ESSAYS ON PUBLIC FINANCE AND TIME USE

by

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CHAPTER I

Introduction

My dissertation focuses on regional economic policy and the utilization of time use data to explore economic behavior. I am interested in how regional economic policy frequently fails to account for unintended consequences, generating impacts at odds with intended goals and how time use data enriches our understanding of economic behavior. I examine these research aims in three papers: I evaluate a federal place-based economic development program for rural areas, I look at the interaction of transportation-based policies of gasoline taxes and public transportation provision through the lens of transportation time use data, and I explore the impact of unemployment on households' allocation of time.

In my first paper, "The Effect of Enterprise Community Designation for Rural Areas, I perform a program evaluation of the federal Enterprise Community economic development program for rural areas. For controls, I utilize communities who applied for, but failed at obtaining designation as well as census tracts that border designated communities. I also attempt to identify economically similar areas through a propensity score matching approach. In the term of evaluation, I find evidence of capitalization of increased services and infrastructure in housing values but little difference between the selected communities and their controls. I conclude that the impact of developing an application for such a program which can lead to local organizational structure, regardless of whether a community is successful in obtaining designation and the benefits that go along with it, may be more important than the program itself.

The next essay, “Pump Pressure: Income, Public Transportation and the Time Use Response to Gas Prices, investigates the responsiveness of time spent in forms of transportation and for different purposes to real gas price changes, the attractiveness of public transportation in a respondents metropolitan area and their interaction. I find the inclusion of an interaction term important in correctly controlling for the effect of gas prices themselves and conclude policy makers should account for dampening behavior impacts gasoline taxes and public transportation expansion can have on each other. It is found that higher levels of public transportation attractiveness, while certainly leading to more time spent in public transportation, does not lead to lower car-based commuting time. The paper also includes a microeconomic model that includes time use and uses empirical data to determine what income groups may have stronger substitution or income effects.

My final essay, “Employment and Intra-household Time Allocation, also utilizes time use data to examine the impact of spousal unemployment and time use on ones own time use. My results are consistent with other studies in finding a very small, but statistically significant impact of about an hour per week added worker effect. I also construct estimates of partner spousal time use where data do not exist to calculate marginal impacts, finding strong leisure complementarity between partners and some substitutability of household production.

By showing the difficulty of enacting meaningful economic development policy in rural areas and the limitations of urban transit policy, I have contributed to the public finance literature by helping to bring to light the difficult realties of policy. In addition, I have explored the time budget set in two of the papers to contribute to public economics and labor issues on topics that generally have relied on other sources of data to provide new light on transportation and household dynamics in the face of unemployment.

CHAPTER II

The Effect of Enterprise Community Designation on Rural Areas

2.1 Introduction

The trend of suburbanization that started at the end of World War II and progressed throughout the second half of the twentieth century caused demographic changes that created problems for many communities in both urban and rural areas. As both population and employment opportunities increased in suburban areas, large cities and rural counties both saw an emigration of population and businesses from their communities. This caused a reduction of tax support and economic infrastructure that eroded growth and forced poverty rates and unemployment rates to levels that were higher than national averages. Isolated from cultural, financial and retail centers and facing structural changes in the agricultural and industrial industries which had traditionally provided employment, rural areas in particular found difficulties in sustaining economic vitality.

In addition to the massive economic revitalization efforts of urban areas of the 1970s, many states in the 1980s created targeted economic development programs to help communities that were lagging within the state. This was usually through a combination of grants to local communities and tax incentives for businesses. In 1993, as part of that year's Omnibus Budget Reconciliation Act, Congress established the Empowerment Zone/Enterprise Community Initiative, a targeted economic development program for urban areas and rural communities across the country. Administered jointly by HUD, HHS and USDA, the program provided block grants, tax incentives and expertise to the designated communities that were labeled "Empowerment Zones" (EZ) or "Enterprise Communities" (EC). Selected communities were then tasked with implementing community improvement strategies they had developed themselves. The Round 1 program designations were made at the end of 1994 with additional communities selected during later rounds between 1998 and 2001.

Using Census of Population and County Business Patterns data, I examine whether the selection as a rural Enterprise Community during the first round provided a significant benefit measured by the economic outcomes of their populations in 2000. Although there has been a good deal of attention paid to the urban Empowerment Zone designation, little research has been performed on the rural communities and none offer cases for proper control groups. I offer a variety of possible control groups, including communities that applied for the initial program but were unsuccessful and communities which were successful in similar competitions in later years. I separately identify census tracts which were similar to selected tracts based on a propensity score match as well as counties which were potentially eligible for selection based on observed 1990 characteristics, but were not involved in applying for the designation.

Compared to other communities which applied to this and similar programs, I find no effects of designation on poverty or employment rates or educational outcomes in 2000. I do, however, find some evidence of higher housing values, indicating possible capitalization of improved services such as health clinics, child care facilities and educational training facilities or investments in community improvements such as water and sewer systems or pollution cleanup. Propensity score matching yields no clear evidence for any findings of positive impacts except for a small decrease in the occupational concentration of the workforce. Additionally, the Enterprise Communities showed slower population growth relative to control groups, although this is not found to be statistically significant in most cases. This paper provides similar results compared to previous research in evaluating targeted economic development programs; that is, findings of efficacy are mixed or hard to find, but there are significant challenges in making accurate measurements. However, this paper is the first to evaluate the rural focus of the federal EZ/EC program. I conclude with remarks on the relative value of the control groups used and a discussion of program theory for economic development programs in light of the results.

2.2 Program Theory and History

2.2.1 Economic Theory of Targeted Economic Development Programs

The economic theory behind spatially targeted economic development programs depends on the tools being implemented. Targeted tax credits can be employed to promote hiring of zone citizens or for any employees of businesses located within a zone, lowering the cost of hiring employees. Alternatively tax benefits for capital investment or regulatory relief can be used to lower costs of doing business. These in turn promote business growth for both new and existing businesses and increase employment (Liebschutz, 1995; Hyman, 1998; Snow, 2000). Some research suggests, however, that tax incentives have little effect on business placement or alternatively are less likely to be employed in labor-intensive firms who have smaller tax burdens (Rubin and Zorn, 1985; Rubin, 1995). Low interest loan programs are also used to provide credit to businesses in order to support expansion and growth.

Job training and education programs targeted towards zone residents can be used to create human capital, making the area more attractive for businesses to locate. Additionally, direct capital investments can "jump-start" the creation of jobs; directly and through the multiplier effect, these investments generate new economic activity that can hopefully be sustained after the project has been completed (Bartik, 2003). More directly, such investment also provides needed low-cost housing, improved roads or other city structures for the community (Wilder and Rubin, 1996). The hope is that these programs can either reverse trends of increasing poverty and unemployment rates or revitalize a community whose economy has grown stagnant through an emigration of human and financial capital.

The policy debate over the desirability of spatially targeted economic programs hinges both on whether or not the programs themselves provide enough help or the correct incentives to promote growth. The development of a national plan for rural economic development has been difficult to achieve for decades, with a lack of consensus stemming from large variation in the needs of individual communities and a lack of agreement by national organizations developed to lobby federal government on behalf of rural communities (Buss and Tribble, 2003). Federal assistance is tasked primarily by the Department of Agriculture, but involves many other departments and super-regional authorities such as the Tennessee Valley Authority. Additionally, even if targeted economic development programs are effective, the question remains whether the programs provide an efficient use of financial and administrative resources. Supporters of the original EZ/EC legislation argued the features of local administration found in the initiative could provide more efficient solutions to local problems because of knowledge of where the money should be spent. Detractors argue that local corruption may reduce efficacy, or alternatively the public funds may simply be funding intra-regional relocation of business activity (Reeder, 1996). This relocation though may still be beneficial if a relative lack of alternative job opportunities and economic need in zone areas are deemed to be more important problems to alleviate (Fisher and Peters, 1997).

An additional benefit of programs such as the Empowerment Zone/Enterprise Community Initiative is that by coming together as a community and developing a strategic plan to address their locale's problems, the citizens are identifying and developing human capital and entrepreneurial skills. This can foster positive conditions for economic growth independent of any benefits provided by national or state governments. President Clinton explicitly touted the benefits of the application process itself to participating communities and regional conferences provided information to local municipalities with regards to how to develop such strategic plans (Thomas, 1995; Aigner et al., 1999).

The national interest regarding locally targeted economic development programs began in the early 1980s, but it was never implemented at the national level during this time. Almost 40 states had some kind of Enterprise Zone program of some form in the years leading up to the federal program(Greenbaum and Engberg, 2000; Wilder and Rubin, 1996). Some initiatives focused on grants and low-interest bond financing to communities, but most used locally targeted economic incentives through job training, tax breaks and access to low-cost capital markets to attract businesses to certain communities. These attempts, however, were not without their critics. Some researchers pointed out the dubious connection between tax incentives and business placement given that labor-intensive firms who would bring jobs have smaller tax burdens and thus less incentive to relocate based on these incentives (Glickman 1984, Jacobs & Wasylenko 1981, Harrison & Canter 1978, Rubin & Zorn 1985, Wilder & Rubin 1996). Wilder & Rubin (1996) surveyed the extensive literature on the efficacy of the states economic zone development programs in the 1980s and found the programs to be generally effective in promoting investment and job creation but still found high variability even with each states programs. They cautioned against the development of targeted economic incentives programs without considering the importance of both the planning stages of local economic development for the duration of the program as well as the cost effectiveness of targeted grants or significant tax breaks.

2.2.2 Legislative History

The first forms of targeted economic development strategies in the United States came with the Model Cities program under President Johnson in the 1960s and its successor, the Community Development Block Grant program which started in 1975 under President Ford. Both of these urban renewal programs focused on providing infrastructure enhancements and other economic development activities to declining cities but were not specifically targeted at localized areas of the cities (Liebschutz, 1995; Mossberger, 2000). Supply-side targeted economic development burgeoned in England during the late 1970s and was championed most prominently by Rep. Jack Kemp in the United States in the early 1980s (Boarnet, 2001; Liebschutz, 1995; Stoker and Rich, 2006). The key component of early forms of these types of legislation in Congress were tax incentives for business who operated within the designated zones. Legislation, however, was never passed, and generally failed to elicit positive responses from Democratic members of Congress who favored more direct forms of government assistance and feared enterprise zones would crowd out other forms of assistance (Hyman, 1998; Mossberger, 2000).

2.2.3 Federal Empowerment Zone/Enterprise Community Initiative

In light of a new-found desire among Congress to help blighted cities in the wake of the rioting in Los Angeles in 1992, the federal Empowerment Zone/Enterprise Community Initiative was passed in 1993 as part of that year's Omnibus Budget Reconciliation Act (Liebschutz, 1995)[1]. The legislation had four aims: 1. increased economic opportunity through job creation and entrepreneurship, 2. sustainable community development without government intervention, 3. community-based partnerships which bring both public and private resources together to address communities' needs, and 4. the development of a coordinated strategic vision bringing together all available social resources for community development (USDA, 1998). Through strategic plans developed at the local level to achieve these goals, the program sought to bring down poverty and unemployment levels and increase investment and business activity in these areas. Federal bureaucratic expertise would be provided in order to assist local leadership with their plan execution and to identify sources of support.(USDA, 1998; GAO, 2004; USDA, 2003). Administration of the program was done jointly through the Department of Housing and Urban Development who oversaw urban areas, the Department of Agriculture who oversaw rural areas, the Department of Health and Human Services for the disbursement of the funds[2], and the Internal Revenue Service who oversaw the tax benefits that would be offered to businesses in the selected communities. Coordination was run through a Community Empowerment Board headed by the Vice President (Rushing, 2000).

For the rural portion of the Initiative, 180 communities submitted applications in a competitive selection process in 1994 with the USDA selecting the designated

[1] A similar program was passed by both houses of Congress in late 1992, but was vetoed by President Bush despite his previous support for the bill (Liebschutz, 1995; Stoker and Rich, 2006).

[2] HHS was involved as the primary administrator of the Social Services Block Grant program through which funds were dispersed to awarded communities. Funds made available through subsequent rounds of the EZ/EC program did not involve HHS.

communities in December of that year (USDA, 2003). Three Rural Empowerment Zones and 30 Enterprise Communities were selected. A list of the selected Enterprise Communities and their state is presented in the Appendix. Communities were defined by individual or groups of 1990 Census tracts, and all areas must have had a minimum of 20% poverty in all tracts with at least 35% in half of the census tracts. There were also guidelines that specified a maximum population and geographic area as well as the criteria for selection which included "pervasive poverty, unemployment and general distress" (USDA, 1998). Designees were selected not just on the degree of need represented by statistical figures but also on the basis of the coherence of their strategic plans and the degree of participation of low-income individuals and community-based organizations (USDA, 1998; Aigner et al., 1998). The USDA also considered both geographic and demographic diversity with and among the designated areas GAO (2004). The program expanded with more Empowerment Zone and Enterprise Community selections in Round II which began in 1999 and Round III which began in 2001. Round III also added a third category of communities called Renewal Communities. Later rounds were characterized by slightly less stringent requirements but also fewer benefits.

The governmental intervention for rural Enterprise Communities was a Social Services Block Grant (SSBG) in the amount of $2.95 million, the ability to obtain tax-exempt bonds, the Work Opportunity Tax Credit[3] to community businesses and preferential treatment in most competitive governmental community development grant programs (GAO, 2010). Access to Qualified Zone Academy Bonds for capital expenditures for educational facilities and tax incentives for private brownfield development were also included. The three Empowerment Zones received a SSBG of $20

[3]WOTC provided a tax credit of 20% of the first $15,000 of wages as well as for some training costs.

million and additional investment and tax credits (GAO, 2010; USDA, 2003). Due to the large differences in treatment between Empowerment Zones and Enterprise Communities and the relatively few number of Empowerment Zones for comparison, this paper focuses primarily on the Enterprise Communities from the first round.

The main purpose of the SSBG was for use as a capital investment to leverage against grants from other sources rather than for funding programs. That is, the grant was to be used to help fund the administration of the strategic plans themselves. The SSBG accompanied with the preferential treatment proved to be the most important aspect of the program as it allowed the community to leverage several sources of funding together. As of June 2000, the leveraging ratio of non SSBG funds to SSBG funds drawn down was 9.8 (USDA, 2003). By 2002 this ratio had nearly doubled to 17.7. These funds have been provided mainly through other federal programs, state governments and from private sector investments for vocational training programs and rural public transit projects, infrastructure improvements, business finance and revolving loan programs and various health, child care and social programs (USDHUD and USDA, 1997; USDA, 2001, 2003). Some communities invested in developing workspace and warehouses for new businesses to move to as well. Communities had freedom to determine what worked best for their strategic plan. Although the Round I designations were initially supposed to last ten years, extensions allowed the program to continue. All rural EZ/EC designations ended in 2009.

What is critical to note is that the call for applications itself could have a significant treatment effect. The development of the application could help a community not only start to identify problems and potential solutions through the development of a strategic plan for economic development, but also foster social interaction and cohesion as well as identify those individuals who could lead a community's economic and business growth efforts. The USDA advocated communities to "create a vision of what the community wants to become in the future"(USDA, 1998). For communities who can no longer depend on agriculture or manufacturing for economic survival, this presented an opportunity and catalyst for everyone to come together and enact change.

This idea led the USDA to grant "Champion Community" status to those communities that were not selected as Enterprise Communities. The Champion Community program was informal within the department but granted similar (but necessarily less) expertise and preference in grant competition solely within the USDA. It is unclear the extent to which communities took up the USDA on their offer, but it provided communities with some assistance in executing their plans for development without the SSBG and tax incentives. Indeed, several designated Champion Communities were selected as Enterprise Communities in later rounds of the program in 1999 and 2002. In 1999, the Champion Community program was formalized and any rural community was permitted to apply for designation with a developed strategic plan. In both cases, the social cohesion that led to the development of an application is an important aspect of the treatment of community designation, representing the non-random selection process. This presents difficulties to the researcher who wishes to obtain unbiased estimates of the effects of the programs themselves through community designation.

2.3 Previous Research on Targeted Economic Development Programs

2.3.1 Evaluations of Previous Programs

No rigorous statistical study has been published on the effects of the Enterprise Community or Champion Community program on rural communities. Two-thirds of states, however, had targeted economic development programs prior to the implementation of the federal legislation (Papke, 1993), resulting in a significant body of literature that sought to evaluate the efficacy of these local programs. As reported in Papke (1993) and Wilder and Rubin (1996), both the results and the methods used to obtain the results have been mixed. Wilder and Rubin (1996) reported a consistent finding in many studies of job growth and increased investment, but that the growth was more apparent outside of urban areas. They note the concern of the quality of jobs that may be moving to these areas as well as the correct interpretation of increased investment. Businesses may not necessarily be responding to the incentives (infrastructure improvements or tax breaks) that an enterprise zone may offer so much as the fact that the designation acts as a signal to businesses of a favorable relationship between a committed government and local enterprise. Researchers used a variety of tools, including surveys, state and locally-collected data, descriptive reports and cost-benefit analysis to evaluate the efficacy of programs run by various states (Wilder and Rubin, 1996).

Bondonio and Engberg (2000) examine the impact of state Enterprise Zone programs on local employment in five states. They use the policy and outcome data from California, Kentucky, New York, Pennsylvania & Virginia and employ random growth rate and propensity score approaches to evaluate the effectiveness of the programs as well as their sensitivity to funding amounts. They were unable to find employment growth related to the designation of zones. Greenbaum and Engberg (2000) perform a similar analysis on housing markets as well employment outcomes for enterprise zones for the same states and find similar results. Papke (1994) found statistically significant reductions in unemployment but also in property holdings for business for Indiana Enterprise Zones, which may have been a result of the inventorybased nature of the tax incentives.

Researchers occasionally come to different conclusions for the same program, even using the same data making it difficult to inform policy makers (Ham et al., 2010). Additionally, variability in precision can generate estimates which are consistent with each other but can lead to different conclusions on findings of effectiveness[4]. Boarnet (2001) in particular stresses the need to educate policy makers about the importance of control groups in determining the relative importance of conflicting research, using his own experience in evaluating New Jersey's Enterprise Zone program as an example.[5]

2.3.2 Evaluations of the Empowerment Zone/Enterprise Community (EZ/EC) Program

Oakley and Tsao (2006) and Busso and Kline (2008) both use a propensity score matching process to evaluate the urban Empowerment Zone program using Census data but come to different conclusions. Oakley and Tsao (2006) found little or only modest improvement in Zone areas while Busso and Kline (2008) find substantial improvements in employment rates and housing market prices. Ham et al. (2010) attribute the difference could possibly be due to Oakley and Tsao (2006)'s use of 1980 data as controls, but notes the reasoning is unclear and the larger issue is that specification can lead to different results given the ambiguous nature of the treatment both in theoretical application, magnitude of effect and geographic impact. As far as this author has found, Ham et al. (2010) represents the only analysis examining the effectiveness of the Enterprise Community program, although they only examined the urban communities with such designation. They did however, examine the three

[4]For example, O'Keefe (2004) which finds a statistically significant short run increase in employment growth for California state enterprise zone, while Neumark and Kolko (2010) does not, although they do mention at least one specification provides a confidence interval which includes O'Keefe's estimate.

[5]Rubin and Wilder (1989) found large job creation as a result of the program using business survey data, but Boarnet and Bogart (1996) found no difference when actually comparing zone and non-zone communities.

rural Empowerment Zones in conjunction with the urban designees. In both cases, they find positive and statistically significant impacts on employment and poverty.

HUD published a study that sought to evaluate the efficacy of the EZ/EC intervention in urban areas over the first half of the life-time of the program, 1995-2000 (Herbert et al., 2001). This interim report, however, only evaluated six enterprise zones. The study found higher job growth than same-city control tracts with similar characteristics in four of the six they examined and commissioned a survey which suggested sharp increases in business ownership rates by residents in all six zones. GAO (2006) also performed an evaluation of urban Enterprise Zones but determined it could not attribute declines in unemployment and poverty rates within the zones to the program. One other study undertaken by researchers at the North Central Regional Center for Rural Development found increased loan availability in all but a few of the rural EZ/ECs, a decline in high school drop out rates in about a third of the communities and increase involvement of community groups in participating in the local EZ/EC corporation during the study period of 1994 to 1997 (Aigner, et al 1998). The study however provided no control group for comparison.

2.4 Data Description

The communities selected as Enterprise Communities and Champion Communities were defined by 1990 census tracts. The tracts were determined using the USDA EZ/EC website[6] and through a USDA FOIA request for the Champion Communities. At least two communities which were awarded Enterprise Community or Empowerment Zone status in later rounds were identified as Round 1 Champion Communities based on information found on the USDA website but were not included in the FOIA

[6]The original website (http://www.ezec.gov) is now offline, although the USDA Rural Development website (http://www.rurdev.usda.gov/BCP-EZEC-Home.html) hosts some of the original information about the communities. Old versions of the EZ/EC website can be accessed using the Wayback Machine at http://www.archive.org.

request. It is possible, then that the list provided may be incomplete. Future research will seek to better information about the identification of Round 1 Champion Communities and subsequent Champion Community status designation when it was officially formalized in 1998. Additionally, I identified the tracts belonging to communities which were designated as Enterprise Communities or Empowerment Zones in later rounds in 1998 or 2001 as well as communities designated Renewal Communities, another type of designation established in 2001. Although this paper does not evaluate those programs, I do use them as a possible control group in one part of the analysis as the application of their programs falls primarily outside of the years of evaluation.

Census Bureau policy is to maintain a fairly even population for each tract, which necessitates changes in the shape and sizes of many tracts between each decennial census so the list had to be updated to identify affected 2000 tracts. The compiled list of tracts was compared to the Census Bureau's Census Tract Relationship Files[7], which identify 1990 Census tracts which have been split or combined to form different 2000 Census Tracts. Affected tracts remained designated so long as the 2000 tract consisted of at least 50% of a designated 1990 tract by population. Additionally, some tract numbers as reported by the USDA as Champion Communities could not be used since they did not exist, providing further indication that the list supplied may not have been completely accurate. As a result, three Enterprise Community tracts and twelve Champion Community tracts did not have appropriate 2000 tract analogues to assign for analysis. This left a total of 156 tracts from 30 communities designated as Enterprise Community tracts and 506 tracts designated as Champion Communities[8]. I also identified tracts which bordered Enterprise Community areas

[7] http://www.census.gov/geo/www/relate/rel_tract.html

[8] The information received from the FOIA request did not provide the groupings of the tracts by application or by community and indicated this information was not available.

by examining spatial maps of the communities.

1990 and 2000 Census data was obtained from the Geolytics/Urban Institute Neighborhood Change Database, which allows users to generate 1990 Census statistics for 2000 tract boundaries, permitting cross-year comparisons. While I would have liked to have used 1980 data to control for long-term trend differences between tracts, this information is not available for most designated tracts as many rural areas such as the ones the Enterprise Community program targeted did not have identifiable census tracts for 1980. The variables used from the 1990 and 2000 Census of Population include measures of population, area, poverty, employment, welfare use, income and education. Population means and standard deviations can be found in Table 2.1. The "Occupational Concentration Index" (OCI) is a measure of the concentration of particular types of jobs as measured by the employment statistics of the Census of Populations[9]. It is the sum of the squares of the percentage of jobs by type as a fraction of total employment. Like the Herfindahl-Hirschman Index, a larger number suggests a higher concentration of workers within particular job types. Whether the result of homogeneous labor supply or a lack of variety of jobs, I suggest that a low variety of occupation opportunities is an indicator of a lack of business vitality and development. Dependence on a single large employer which may induce a low OCI may have some benefit to a community as a second-best option, but business variety promotes market competition and conditions on the demand side of the labor market among employers that can lead to higher wages and employment. I recognize, however, that the nature of industries and labor markets in rural communities does not necessarily make this a strong metric of labor market

[9]The Census splits 16 and over employed persons into 9 occupations: 1.professional and technical occupations, 2.executives, managers and administrators, 3.sales workers, 4.administrative and clerical support, 5.precision production, craft and repair workers, 6.operators, assemblers, transportation and moving material workers, 7.non-farm laborers, 8.service workers, and 9.farm, forestry or fishing workers.

strength.

I also utilize County Business Patterns data of total employees and total payroll, calculating the payroll per employee for various years before and after treatment. This value is assigned to each tract within the county. While this is likely not an accurate measure of economic activity at the tract level, it is relevant as a measurement of available job quality in the area near the enterprise community of which zone citizens can take advantage. Considering tract level business establishment data is not available, it may be also be a best approximation of a tract level measure of job quality, however it may not be a very good one. Figure 2.1 charts the ratio of 1990 tract level unemployment for the Enterprise Communities with their county level unemployment which shows a skew above a ratio of 1 with a mean of 1.25 and a median of 1.16. Of note, however is that two enterprise communities in particular, La Jicarta in Arizona and Halifax/Edgecombe/Wilson in North Carolina include tracts with 7 of the 9 largest ratios. Regardless, I utilize this measure to control for the quality of jobs available before and after the designation. A desire for better yearly data for population and economic statistics is strong, but only recently has such data been made available for urban areas through the American Community Survey. Systematic nationwide data collection for rural areas outside of the Decennial Census of Populations has and likely will remain a problem for many years to come.

2.5 Evaluation

In addition to problems of acquiring data for these types of area, part of the reason it is difficult to perform econometric analysis for program evaluation purposes for economic development programs is identifying a proper control group. If an identified control group is identical to the treatment group on observed and unobserved variables, a simple difference-in-differences approach would be appropriate. However, the concern with any such evaluation is that assignment is not random. Unobservable variables then could affect treatment assignment which in turn could affect future outcomes, biasing estimates of the effectiveness of the program itself. Additionally, there is the problem of identifying eligible communities that would be similar enough to form a comparison group if the program had not been applied. It is important to account for these factors to prevent assignment of program effectiveness (or ineffectiveness) to economy-wide trends that may be the real drivers of economic outcomes; frequently, locally produced reports claiming jobs produced fail to account for these counterfactuals at all, generating misleading results (Bartik, 2002).

To alleviate the first concern about non-random assignment, I utilize three control groups: tracts which received Champion Community designation after failing to be named Enterprise Communities in Round 1, tracts from rural communities that received Enterprise Community or some other federal zone designation in later years and all census tracts in states which hosted an Enterprise Community. In order to make comparisons against communities which are most similar to Enterprise Communities on observables related to designation selection but who did not generate strategic plans, I identify two comparison groups of areas that had not received any federal economic development zone designation. I perform a propensity score matching approach and separately identify comparison counties through manual selection using statistics identified as related to eligibility and selection for designation.

In subsections 2.5.1, 2.5.2 and 2.5.3, I seek to identify the treatment effect of Enterprise Community designation for communities which are pre-disposed to developing and following through with strategic plans. In subsections 2.5.4 and 2.5.5, I identify the treatment effect for the treated communities but will not account for the unobserved variables related to having resources available to generate an application. The interpretation of the two types of comparisons will be different. The comparisons to similarly treated communities measure the effect of the Enterprise Community program designation, conditional on applying for the program, or alternatively, conditional on the community having the capabilities of developing a strategic plan. The comparison made on communities matched on observables related to designation selection measure the combined effect of both developing a strategic plan necessary for application for a federal targeted economic development program as well as the effect of the program itself. Since the quality of their strategic plans (as judged by the USDA) was a factor in selection, these estimates could be biased upward, if USDA-judged higher quality strategic plans are more effective[10].

2.5.1 Comparison to Champion Communities

By identifying tracts that were part of communities which applied but did not receive designation, I can control for aspects of communities which further the generation of applications and strategic plans in the first place. The summary statistics in Table 2.1 show Champion Community tracts as slightly better off in 1990 than Enterprise Community tracts, although not substantially so. Poverty and unemployment rates are somewhat lower in Champion Communities, although median incomes and housing prices are slightly lower as well. The communities are fairly similar on initial economic characteristics, but the true value of Champion Communities is their ability to act as controls for the unmeasured variable of applying for Enterprise Community status and developing a strategic plan. Certainly it is true that Champion Communities would execute and further develop their strategic plans to varying degrees; as discussed above, it is unclear what the actual "alternative"

[10] Of course, this bias could also run in the opposite direction

treatment these communities received. However, this comparison helps to control for the unmeasured "strategic plan" effect which should be correlated with positive economic development and growth and would upwardly bias the estimates of any positive effects of the Enterprise Community designation.

Table 2.2 shows the raw means differences between the 1990 and 2000 Census measurements of the eleven outcome measures examined in the analysis for the Enterprise Communities and various potential control groups. Group mean differences denoted in bold are significantly different from the Enterprise Community mean (column 2) at the 95% confidence level. Without controlling for 1990 levels, tracts located within Enterprise Communities face smaller increases in median home values compared to all other types of tracts and larger decreases in government assistance rates compared to Champion Communities and tracts which border Enterprise Communities. Additionally, poverty rates and unemployment rates also decline more compared to border tracts. On average, Enterprise Communities also grow slower in population than other designated tracts and statistically significantly lower than surrounding tracts and the rest of the country.

To control for the difference in 1990 levels between different types of communities, the following equation is estimated:

$$Y_{2000i} = \alpha + \beta EC_i + \gamma X_{1990i} + \epsilon_i, \tag{2.1}$$

where Y_{2000i} represents the 2000 outcome variable of tract i, EC_i is an indicator variable representing Enterprise Community status for tract i, X_{1990i} is a vector of 1990 characteristics. A list of the controls utilized in the regressions in this section can be found in the Appendix and whose coefficient estimates will not be reported for space.[11] These include employment, education, poverty and racial characteristics as well as Payroll per Employee for the parent county of the tract reported by County Business Patterns for 1988, 1990 and 1992. The payroll per employee is used as a measure of the quality of jobs in and around the tract. All 1990 estimates of the relevant 2000 outcomes used for evaluation are used as controls in all estimation procedures utilizing Equation 2.1.

Table 2.3 shows the results of this regression for eleven 2000 outcome variables on Enterprise Communities and Champion Communities only. The top row of each half includes all identified tracts designated as Champion Community in Round 1, while the bottom half of each row is restricted to Champion Communities which did not receive any other program designation in later years. The coefficients estimate the effectiveness of the Enterprise Community relative to the informal USDA Champion Community program.

Among these communities who applied for Enterprise Community designation, achieving selection has no effect unemployment and overall poverty outcomes of 2000. An increase in housing values is found to be significant using both identifications of Champion Communities with EC designation generating a 4% increase. Since uncontrolled difference-in-differences comparison showed a *smaller* increase in median home value prices over the time frame, there is strong indication that the designation is providing some of the effect. Also, significantly larger decreases in the government assistance rate shown by the differences-in-differences approach disappears when controlling for 1990 observables. There are also weak indications that EC designation improved child poverty rates and median family incomes compared to unselected communities, with results more favorable to Enterprise Communities

[11]Coefficient estimates for the controls from this and any other regression are available upon request.

compared to the difference-in-differences comparison. Differences on educational measures are small and not significant. Population changes are smaller in designated communities relative to Champion communities, but the effect is not statistically significant.

The increase in median housing values may be based on the expectation that the Enterprise Community designation will generate economic growth in the future but the lack of any findings of improvement in unemployment or poverty rates is troubling. More likely, the differential increase in housing values represents a capitalization of increases in services or infrastructure improvements available to residents of designated tracts as a result of the Enterprise Community status. The 2000 Executive Summaries filed with the USDA of several of the Enterprise Communities reported utilizing funds for improvements of sewer and water systems as well as funds to rehabilitate the existing housing stock. Additionally, many communities developed job training and education programs and several increased the availability of public transportation (USDA, 2001). These improvements may or may not generate improvements in employment or poverty conditions in long-term; it may be conditional on the ability of these communities to sustain funding for programs after outside funding is exhausted. However, they do make the community more attractive, which in turn can increase housing values.

The lack of differences seen in unemployment and poverty rates are not entirely unexpected considering a significant reason Champion Communities were not selected is because they were better off than their Enterprise Community counterparts. Even if the Enterprise Communities achieved gains, Champion Communities could have achieved parallel gains based on unobservables that generated their rejection, such as not showing significant enough signs of distress. If communities employed long term strategies, especially given the goal of the initiative which was to promote self-sufficiency, progress may also take time to develop. One final interpretation is that the benefits of Champion Community status, which originally was informal USDA assistance and some preferential treatment for grant programs within the department (as opposed to government-wide for Enterprise Communities), were providing similar effects as the Enterprise Community status.

2.5.2 Comparison to Any Rural Federally Designated Community

Equation (2.1) was then estimated on the population of identified tracts which received Champion Community[12], Enterprise Community, Empowerment Zone or Renewal Community designation during *any* round of selection in 1994, 1998 or 2001. The results of those regressions are found in Table 2.4. The interpretation of the reported coefficient on Enterprise Community designation is the effect of the program relative to communities who had then and future capabilities to apply for USDA economic development programs. A more appropriate control group would be tracts from *any* community which applied for any USDA designation during the three rounds of competition to distinguish the benefit of making an application relative to generating a successful application. Inquires into such information suggested it was not available.

Unemployment, poverty rates and educational outcomes fail to show any evidence of an effect of Enterprise Community designation, although again we see some signs of housing values increase. Again, this indicates there may be some capitalization of improved services or infrastructure as a result of the funding produced by the designation and the magnitude is similar to that found when compared to just the

[12] This current draft uses an incomplete list of Champion Communities when the program was formalized in 1999-2000, culled from the original FOIA request and lists of current Champion Communities on the USDA website. The author is in the process of trying to acquire a more complete list for this paper and potential future research on the efficacy of the Champion Community program.

Round 1 Champion Communities. Additionally, there is a statistically significant increase in payroll per employee of 1.8% for Enterprise Communities, indicating some evidence that positive labor market outcomes are occurring as a result of designation. The increase in payroll per employee is also larger and more precisely estimated compared to the CC only regression, but may also indicate the members of the other selected programs may have had worse economic outcomes during the 1990s compared to EC communities and thus were more attractive for future program selections in later years.

2.5.3 Comparison to All Tracts and Neighboring Tracts

To examine the effect the Enterprise Community status relative to all other communities and to investigate the existence of any potential spillover effects into neighboring communities, I then estimate the following regression on all tracts in states that held a round 1 Enterprise Community designee:

$$Y_{2000i} = \alpha + \beta_1 EC_i + \beta_2 CC_i + \beta_3 SURREC_i + \gamma X_{1990i} + \epsilon_i. \tag{2.2}$$

Indicator variable CC_i denotes if a tract is located with an identified Champion Community and $SURREC_i$ denotes if a tract is located on the border which surrounds an Enterprise Community designated tract. If the regression is properly specified, these regressions can provide estimates of the effect of Enterprise Community designation compared to any other tract (although this would be inclusive of the "strategic plan effect") as well as any average spillover effects to neighboring communities. Economic theory does not suggest these spillover effects should necessarily be in any particular direction. If the targeted nature of the program only attracts "local" investment and business from neighboring communities and thus only facilitates an (economy-wide) inefficient transfer of economic activity, the spillover effect could be negative.

Conversely, if the program generates new economic activity, there could be positive spillover effects.

Tables 2.5 and 2.6 provide the results from the eleven 2000 outcomes with and without state control variables. Enterprise Community designation appears to provide strong declines in the unemployment rate, increases in median family income, declines in occupational concentration and declines in poverty. However without 1980 data, it is unclear if these results are merely displaying regression to the mean. Each coefficient estimate for the surrounding tracts are of the same sign, but of smaller magnitude relative to the designated tracts, possibly indicating some positive spillover effects. It is also important to note that the EC and CC coefficients for *all* regressions in Tables 2.5 and 2.6 also have the same sign indicating both programs on an empirical basis are performing the same functions on the outcomes, even if the relative degree is unclear.

2.5.4 Propensity Score Matching

The above approaches compared tracts within Enterprise Communities to tracts within other communities that established the capability of forming a community group to develop a strategic plan and implement it. They then show the effect of the EC status relative to communities what had applied and/or been accepted for federal programs that required a strategic plan. Outside of the informal help provided by the USDA to the Champion Communities, the implementation of the later rounds of designation did not occur until at least 1999, so any differences found can be attributed to the effect of the EC designation for this subset of communities. As discussed in the program history, however, the inducement to generate a strategic plan is part of the social benefit of having these types of competitions. Another useful estimate for policy makers then is the value of the Enterprise Community program inclusive of any effect generated by forming a local economic development corporation. The propensity score matching and "matched" county approaches provide estimates of such an effect by identifying control groups of similar communities to those which were recipients of the initiative, but who did not apply. This wla

Propensity score matching was introduced by Rosenbaum and Rubin (1983) and detailed in Wooldridge (2002) and Heckman et al. (1997). It aims to act as a randomization process by estimating the conditional probability of selection into the program based on pre-treatment observables and then compare each treated tract with one or more untreated tracts that have similar estimates of the likelihood of selection. In general, in a program evaluation, one is interested in the average treatment effect on the treated (ATT) which is defined as:

$$ATT = E[Y(1)|D = 1] - E[Y(0)|D = 1], \tag{2.3}$$

where Y(D) represents the result of the outcome variable and D equals one if tracts are treated and 0 if they are not. The researcher's problem is that the outcomes of the treated if they had not been treated needed to calculate $E[Y(0)|D = 1]$ are not observed. The estimates found in the three sections above do provide a control group that can be used to identify the ATT but only when the treatment is defined as receiving designation given you have developed a strategic plan. Those tracts are not useful measures of untreated tracts if we want to also estimate the effect of making a strategic plan as well. Since we cannot measure the untreated outcome of the treated, one alternative equation to consider then is the difference between the treated outcome of the treated and the untreated outcome of the untreated :

$$E[Y(1)|D = 1] - E[Y(0)|D = 0] = ATT + E[Y(0)|D = 1] - E[Y(0)|D = 0]. \tag{2.4}$$

This equation states that the observed difference between the treated and untreated is equal to the average treatment effect on the treatment plus any selection bias occurring due to selection not being random. If the Conditional Independence Assumption is satisfied, then the selection bias is zero and we can simply examine the difference in outcomes of the treated and untreated. In this context, the Conditional Independence Assumption does not require selection to be completely random as would be required for a simple comparison, but does statet that the likelihood of Enterprise Community designation depends on pre-treatment observed variables. The propensity score approach estimates a probability of selection based on these observed variables and then a researcher chooses a selection process to match designated tracts with undesignated tracts that have similar likelihoods of selection. If the probability of selection is correctly estimated and appropriate matches are found for the estimated propensity scores, the selection process will satisfy the Conditional Independence Assumption.

The Conditional Independence Assumption will be violated if the goal is to solely estimate the impact of the program as each of designated tracts were part of communities who must have generated an application and the variables which cause application generation are unobserved. However, if we redefine the treatment to include having the local social capital and interest to develop a strategic plan that helped obtain designation, the necessary support from state and local governments *as well as* the Enterprise Community program itself, it may be more reasonable to attribute unobserved selection bias to randomness. Given this definition, the propensity score approach will still produce a valid estimate for the average treatment on the treated (ATT).

I employ the matching process using the STATA command psmatch2[13] using

[13] E. Leuven and B. Sianesi. 2003. "PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing". http://ideas.repec.org/c/boc/bocode/s432001.html. Version 4.0.3.

nearest neighbor with replacement and radius matching separately. I choose to use replacement with nearest neighbor matching as there are only a small number of untreated tracts which can be used to match when propensity scores are high. This will reduce selection bias by not forcing a matches that may be far away in propensity score (as would occur without replacement) but will increase the variance of the estimator (Smith and Todd, 2005). Radius matching is used to increase the number of available matches for comparison by choosing all untreated matches within a certain radius of the propensity score of the treated tracts. This process also will increase the variances of the estimates (Dehejia and Wahba, 2002).

Only designated tracts which were located within the common support were utilized in order to make proper comparisons. Observations whose propensity score were higher than the maximum score of the untreated tracts were dropped. An initial logit regression was run to estimate the probability of a tract being selected as an Enterprise Community. The logit was performed using all tracts located in states which had an Enterprise Community[14], excluding communities which were used in the control group for Subsection 2.5.2.

As performed in propensity score matches evaluating the urban Empowerment Zones in Oakley and Tsao (2006), Busso and Kline (2008) and Ham et al. (2010), including 1980 or earlier data controls for long-term trends which show that there are significant difference between selected and unselected or matched communities in long term trends. For example, if selected communities have seen unemployment and poverty rising faster compared to matched communities, even if 1990 levels are similar, this could bias the results of the Enterprise Community towards showing no effect or a detrimental effect on these outcomes. Unfortunately, my choice of

[14] Using tracts for all states did not materially affect the results of the logit regression, but could potentially increase the likelihood of "matched" tracts being dissimilar on unobservables and thus were not used.

data in utilizing the NCDB prevents the use of 1980 Census data for many rural areas. Future extensions or refinements of this research may seek to address this shortcoming using alternative data sources, however in addition to using the log pay per employee for 1992 in the selection regression, I also include the change in growth in pay per employee for the county in which the tract is located from 1988-1992. The inclusion of this variable will help control for the possibility that trends in labor market strength are part of the "general distress" that was an element of selection.

The results of the initial logit regression with the covariates used to estimate the probability of selection are found in Table 2.7. Most variables have the expected sign on probability of designation; coefficient estimates of unemployment, government assistance rates and poverty rates are positive and pay per employee is negative. Oddly, proportion of those living below 50% of the poverty line is negatively correlated with selection, however this may indicate extremely poor communities may not be in eligible rural areas or do not have the social capital for development of an application.

As per Rosenbaum and Rubin (1983), propensity score matching is valid if selection on observables the matching is successful in identifying control tracts which are similar on the variables identified that are used for selection. Tables 2.8 and 2.10 show the means of the treated and control groups and reduction in bias due to the matching procedures. Radius matching is performed with a caliper of size .01, meaning all untreated tracts within a propensity score of .01 of each treated tract are used for comparison. No significant differences for any of the utilized 1990 variables were found. Additionally, low pseudo R^2s and chi-square tests for joint-significance of the probit model of selection run on the matched samples also support the claim the model controls for the covariate bias well.

Tables 2.9 and 2.11 show the results of the difference in means of the treated tracts and the entire sample for 2000 outcomes and the difference in means of the treated tracts and matched tracts evaluation of the statistical significance of the average treatment effect on the designated communities. No outcome shows any significant difference between the enterprise communities and the matched controls in the one-to-one matching procedure, while the radius matching finds statistically significant differences with *lower* median housing values, lower payroll per employee for the treated tracts and increased occupational diversity. The propensity score matching finds no effect for Enterprise Community status on employment. The radius matching also finds mild increases in poverty and government assistance rates and decreases in population growth indicating a detrimental effect of designation. Alternatively, the propensity score specification does not control for long term trends and the enterprise communities may be tasked with reversing long-term declines that the matched communities were not facing. Unreported results examining the estimate of the difference in differences between 1990 and 2000 outcomes as opposed to the reported difference in means do not show meaningful differences in results.

2.5.5 "Matched" Counties

The application process, implementation and evaluation of Empowerment Zones and Enterprise Communities has been made difficult by the fact that the initial round required specific boundaries for population, area size and poverty levels for included tracts. This meant that certain tracts located near the application tracts were excluded from the program who otherwise would have culturally, politically or economically would be considered part of the "community." Additionally, analysis generally has to be performed on a tract by tract basis since communities are rarely defined by any political boundary. This also makes difficult the act of identifying "communities" which could have applied for the program but did not. Spatially identifying groups of tracts likely ignores political or economic boundaries which may have made such community forming appropriate or inappropriate and frequently, the tracts of actual Enterprise Communities were not contiguous and located across multiple counties or even states. Further discussion of how this may affect the interpretation of the results of this evaluation is found in the last section.

In further pursuit of identifying groups of tracts that could have applied but did not, I examined the 1990 characteristics of counties to determine which counties may have been eligible to apply. Although actual Enterprise Communities generally spanned several counties, or alternatively only covered a fraction of a single county, county-level governments frequently helped oversee the reigning local development corporation in charge of the Enterprise Community, making it an appropriate and convenient grouping of census tracts to examine. After identifying counties that were likely eligible for application, I then compared them to "Combined Enterprise Communities" consisting of population-weighted average or total statistics of each communities' designated tracts.

I examined the 1990 statistics of each county and eliminated any county which did not pass certain justified rules I created based on 1990 Census characteristics. Counties must have an overall poverty rate above 30%. By rule, all Enterprise Communities must have 25% poverty in 90% of tracts and 35% poverty in half of tracts. Included counties must have a density below 100 persons per square mile. This ensures the county is sufficiently rural and in practice, all but one Combined Enterprise Communities had density below 100. Total county Area need to be below 5000 square miles. By rule, all applied communities had a maximum of 1000 sq. mi., although this was not followed in practice; some Combined Enterprise Communities surpassed this amount. Total county population was required to be below 100,000 persons; all Combined Enterprise Communities had populations less than 100,00 and by rule the maximum population was to be 30,000, but again this was not followed strictly. Additionally, government assistance rate for the county needed to be above 5%. There was no rule for this for the application, but communities did need to provide a general indication of distress and all Combined Enterprise Communities showed take-up rates above 5%.

Two other rules were employed to ensure the selected counties were similar to those selected but did not receive a treatment. All counties which included census tracts that received some other rural federal zone designation such as later round Enterprise Community, Empowerment Zone or Renewal Community or any identified Champion Community from any round were removed. Additionally, counties for which the population was more than 20% American Indian were excluded. Communities that primarily consisted of American Indian reservations were not eligible for Round 1, although they were for subsequent programs and were frequently selected.

This left fifty "matched" counties for comparison with the thirty combined enterprise communities. A comparison of 1990 summary statistics can be found in Table 2.12. No County Business Patterns data are used since there was no way to assign a relevant figure to the Combined Enterprise Communities with any degree of accuracy. Many Enterprise Communities consist of tracts from several counties and, as discussed previously, the data is as useful as a measure of labor market quality within the designated tracts, but instead as a measure of quality in the county-wide area of the tracts. The table does show significant differences between the two sets of counties/communities, with the matched counties exhibiting much lower average housing values and average family incomes as well as higher poverty and welfare rates. So, on average the "matched" counties were likely worse off than the combined enterprise communities. This matching did not produce communities with similar statistics as the propensity score matching; however this was not the intent. The intent was to identify communities which on several metrics met the eligibility requirement but did not apply. On observables, the higher levels of distress may point to a community without the social capital or leadership to generate an economic development plan for application. Although the high variability of county and combined Enterprise Community density does not show a statistically significant difference between the means of the two groups, the mean of the "matched" counties is 60% less than that of the enterprise communities. The lower density could conceivably be a deterrent to the political and social relationships needed to generate a strategic plan.

Table 2.13 shows the results of regressions estimating Equation 2.1 on the "matched" counties and combined enterprise communities with the same 1990 controls[15] used as the previous regressions except average housing values and family income are used for the county/community and no County Business Patterns statistics. The only significant difference between 2000 outcomes for the two groups when controlling for 1990 observables is found in the OCI which is significantly smaller for combined enterprise communities. Additionally, signs for the Enterprise Community designation for unemployment, high school dropout rate and poverty rates are all positive, possibly indicating the program's effect was either negligible or detrimental. A more likely possibility however is that the "matched" communities may have experienced a reversion to the mean that surpassed the Enterprise Communities due to their lower initial standing, however utilizing earlier data would provide a better confirmation of such a phenomenon.

[15]See Appendix for list.

2.6 Discussion

The results of the above evaluation do not show a significant effect of the program on unemployment during the time frame examined, but there are signs that the program may have provided positive benefit. Median home values were significantly higher in enterprise communities compared to communities which which applied but were not successful in receiving designation in the first round as well as higher than communities which received similar designations in future rounds of competition in 1999 and 2001. It is possible then that either that there was an improvement in housing quality or housing values capitalized increases in social services and infrastructure improvements funded by the Enterprise Community program. These increases in housing prices parallel similar findings in urban Empowerment Zones by Busso and Kline (2008). Population trends, however, in the last half of the 1990s relative to the control groups indicate that the selected communities were successful in sustaining population growth in line with other communities. Further examination of the population changes of subgroups in a longer timeframe will provide a better picture as to whom the communities may be attracting or repelling relative to others.

These estimates are appropriate for determining the average treatment effect of being awarded designation conditional on applying as they control for having the capability to develop and actualizing strategic plans for submitting an application. As this process could generate positive benefits itself, the estimates from the first two comparison groups are most closely related to the actual effect of designation. It is unclear whether Champion Community status or future program designation would bias these estimates in a particular direction. Champion communities may be better off relative to Enterprise Communities by virtue of them not establishing enough economic distress for selection, but also may not have developed an attractive enough strategic plan. Similarly, future designated communities may have seen further decline in the 1990s inducing them to apply in later rounds or ”creaming” of the first round of Empowerment Zone/Enterprise Community selection led them to be selected with better economic conditions. Observed sample means from 1990 suggest the control tracts from the first two comparison groups were better off compared to Enterprise Communities leading to downward bias for estimates of any beneficial effects of designation. That said, a variety of 1990 controls were used and coefficient estimates for the effect on unemployment and poverty rates were small in magnitude.

Compared to all tracts in states with an Enterprise Community, designation appears to have a significantly negative effect on unemployment, poverty and occupational concentration and a positive effect on median family income. However, this estimate does not control for the "application effect" and may also include the effect of having the capability to make a strategic plan. The combined effect then would be expected to be of larger magnitude compared to the estimates from the first two control groups. While this could be attributable to mean reversion, it may support the claim made by President Clinton and others that the application effect generates benefits to the community even if the effect of the program itself can't be found. Additionally, the magnitude of the increase in median housing values was lower when compared to all tracts and not statistically significant. However, this could still be consistent with the other regressions if housing values are increasing at higher rates in non-treatment tracts and the effect of the zone designation kept pace with those increases whereas it would have fallen behind otherwise.

Signs on indicators for tracts which border Enterprise Communities have the same sign as designated tracts which may indicate intra-community transfers of business activity are not occurring as warned about in Bondonio and Engberg (2000). It could be argued that this is less likely to occur in rural areas since the costs of moving a business and employees between tracts is much larger in rural compared to urban areas due to increase distances between population centers. However, it may still be possible that transfers of business activity are occurring on a larger spatial area than examined.

The propensity score matching and “matched” county procedures also did not produce identifiable differences as a result of Enterprise Community designation for unemployment or poverty levels. Both procedures showed decreases in occupational concentration, indicating workers are reporting participating in a wider variety of types of jobs and potentially a wider variety of industries that could promote long-term stability. Interestingly, the radius matching propensity score approach found a significant *reduction* in median housing values associated with enterprise community designation which may call into question the results from the OLS comparison group regressions. If there was a significant positive effect of both the leadership required to form an application and the designation itself, it could be expected that the results from the propensity score matching would be greater than the comparison to Champion Communities. However, this did not occur.

It is important to revisit the question of whether we should expect economic changes due to this program in the first place. As discussed in the program theory section, the Enterprise Community Initiative for rural areas consisted of employer tax credits and a start-up grant to leverage for other sources of money in local private of public sector as well as preferential treatment in federal grant programs across the government. Although the specific program designs were developed by local communities, federal government administrators and local agencies themselves frequently touted the successes of job training programs, housing construction and revolving loan funds for businesses (USDHUD and USDA, 1997; USDA, 2001). Other grant money was available through alternative competitive processes in which they were provided preferential treatment, but the availability of federal funds is limited to the scope of the programs. This may or may not be restricting in practice, but the local development corporations are working under more constraints than a large lump sum grant.

It is also possible that any tax benefits may not be effective. In reports generated by the GAO and HUD on the urban Empowerment Zones, they found large businesses, in particular those with over 500 employees, were much more likely to be aware of and take advantage of tax credits (GAO, 1999; Herbert et al., 2001). This is credited to having better expertise to tax filing and having the profits that necessitate using the tax credit, and thus it is unclear if this then is useful to smaller businesses in rural areas to the extent we would see employment growth.

This choice of how the address local problems of unemployment and poverty was made at the local level in hopes of better taking advantage of local institutional knowledge and to avoid a "one fits all approach." A GAO interim report of urban Empowerment Zones cited poor economic conditions and lack of human and physical capital as problem areas the local stakeholders wanted to address (Herbert et al., 2001). However, while there were varying combinations of promoting business versus workforce development being put forward as tools for achieving their primary goals, the communities sought these tools with the secondary purpose that they would also in turn allay crime, racial problems or physical conditions. The report noted, though, stakeholders frequently remained ambiguous about how that was to occur. Rural enterprise communities report a variety of different approaches such as training for loan procedures for businesses and potential homeowners and creating business centers to educate businesses owners on federal programs and tax incentives. Decreasing the costs of employment for workers were also made possible through transportation arrangements, child care and skills training (USDA, 2001).

While the application of programs was not consistent across communities, the statistics used for the selection process and the choice of programs developed by communities indicated business and employment growth and poverty alleviation were main concerns for local and national stakeholders. This paper's findings of little evidence of improvement in these areas once control groups are identified may be disconcerting for policy makers. Empirically, however, Bondonio and Greenbaum (2007) describe how null-mean impact analysis may bely more complex processes taking place. They note increases in employees, sales and capital investment by new and existing businesses could actually be offset by zone-induced closures by inefficient businesses, leaving behind stronger firms. That said, "foot-loose" low-wage business may take advantage of tax incentives to relocate and then move on when a better offer arrives (Rushing, 2000). Another type of bias that could occur is that growing firms are more likely to take advantage of the tax benefits and other assistance provided by targeted economic programs, but these firms are more likely to grow in the absence of such benefits, providing an upward bias on the effects of the program Bartik (2002). It is unclear, however, if these theories and findings would apply in the same fashion to rural communities.

A related empirical question raised by the above findings is if differentiation in funding levels generated by the local communities produces disparate outcomes by 2000. I collected the total funds obtained by each Enterprise Community as reported in posted Annual Reports from 2001 from the USDA EZ/EC website.[16]. Table 2.14 reports the same 9 (non CBP) 2000 outcomes with the following regression using the same 1990 controls as in Table 2.13:

$$Y_{2000i} = \alpha + \beta ln(F_i) + \gamma X_{1990i} + \epsilon_i \tag{2.5}$$

where F_i is the reported funding. The estimates show increases in funding have a positive effect on average housing values in the community, but also positive effects on poverty rates. To interpret these results, it is important to note that decisions on funding, which were based on applications made to governmental grant programs after designation, may be made based on poverty conditions that were more closer in measure to the 2000 Census than 1990. It is very possible then that Enterprise Communities with larger increases in poverty during the 1990s may have indicated higher distress levels that resulted in more funding. As such, it is unclear what direction the causality would go. Additionally, while higher housing values may indicate growth or a capitalization of future expected growth, it may also be correlated with sources of human capital that would attract private investment into the development corporations or grant money from state or federal governments. It should be noted that an examination of the correlation between funding and 1990 levels showed evidence only HS graduation rate ($\rho = -.419$) and proportion of population that was white ($\rho = 0.483$) were related to the amount of funds. A regression of 1990 statistics on funding showed no significant correlation. It is unclear, however, that marginal funding levels would have an affect on 2000 outcomes as employment and anti-poverty programs could take months or years to establish and years for evidence of effectiveness to develop.

[16]See footnote 6.

2.6.1 Strategic Plan Development

Another issue to consider is that developing the initial strategic plans was problematic for many communities. Thomas (1995) detail the problems in developing the strategic plans, including inconsistent lists of plan elements communities could include that were provided by the federal government and contradicting advice made by HUD and USDA representatives about what was important for the application evaluation. Additionally, many communities experienced difficulties establishing local community development corporations to be the lead organization, particularly if it was not being done at the county level. Aigner et al. (1999) cite problems specifically within the rural areas with building trust within a variety of potentially competing stakeholders as well as differing communities that do not fall along tract boundaries competing with each other within a zone/community. Later on, many rural enterprise communities reported turnover in the staff and leadership of the lead economic development corporation as a inhibitor to progression in executing their strategies (USDA, 2001). In rural areas, it is clear a relative scarcity of entrepreneurial skills and leadership ability can make locally administered development plans problematic. Conversely, rural communities also experience idiosyncratic problems which require locally tailored solutions such as resistance from militia groups in the Lake County EC, Michigan, drought and damage caused by the Cerro Grande Fire in the La Jicarta EC of New Mexico and interracial conflict in the North Delta Mississippi EC and Northeast Louisiana Delta EC (USDA, 2001)

Another hurdle some communities faced was determining the boundary definition of their communities. Only half of the selected communities were wholly within a single county. Communities ranged from being defined by a single tract (Santa Cruz, CA and East Prairie, MS) to 10 tracts spanning 6 counties (Central Savannah

River Rural EC in Georgia). Of those ranging over multiple counties, several were still contiguous, although most were not. The political processes which generated these boundaries were constrained by the program's tract-level and community level poverty requirements[17]. This could generate problems for the implementation and efficacy of any strategic plan. If tracts which are more economically healthy are not included, stakeholders, political entities, and community organizations in those tracts or whose constituencies may lie in both included and non-included tracts may be less willing to provide resources. Additionally, if selected tracts do not represent a clear social community, both implementing and measuring the impact of health, vocational and child care programs (among others) may be problematic. The tract residency of those in need, the tract location of where such services are desired (say, near a place of work) and the tract location of where such services could be most effectively provided (for example, near an existing health care facility) may all be different.

On the other hand, the political reasoning to prevent non-high-poverty tracts from being included does provide some suggestion that allowing for more pre-existing well-defined communities is not necessarily beneficial for the intended targets of the program. Presumably, high-poverty tracts are targeted because they are the ones most in need. If tracts with less poverty are included, stakeholders from those tracts may end up being more likely to dominate strategic plan and community development board decisions. Additionally, the inclusion of several stakeholders over a wide range of political communities may generate regional cohesion and cooperation which may not have otherwise existed[18]. Of course, disagreements over disparate priorities could

[17]Thomas (1995) details the difficulties similar federal requirements generated for applicants of the urban Empowerment Zones.

[18]During the application process, states varied as to their level of involvement. Some local communities recieved no help from the state in their application formation while other states took the lead in community formation.

certainly evolve from such discussions as well.

An example that illustrates further potential trade-offs of using poverty-rate-restricted tracts or existing political boundaries is the employer tax credit. If businesses are encouraged to move from non-designated to designated tracts as a result, this is a gain for the designated tract, but possible efficiency reducing for the overall community, particularly if the move is simply across town or across county. If a larger or more coherent geographic area is used, such distortions (within the local economy) may be avoided and businesses may still seek to hire additional workers. The distortion could even go the other way as business, despite the tax credit, avoid designated communities because of stigma that they are economic deficient in some way. Additionally, if efficiencies of agglomeration economies exist locally, providing incentives for business and individuals to remain within or move to selected tracts instead of relocating to more dense and potentially more economically sustainable locations could stunt the development of the regional economy.

Therefore, the analysis performed in this paper may be affected by the choice of tract eligibility requirements. The results measure the impact of generating an application and receiving designation *conditional* on the communities meeting the tract-level requirements described by Congress. The results do not control for differences between and within Enterprise Communities, Champion Communities and unapplied communities faced in application and community formation because of these requirements. As mentioned above, reversion to the mean for the highest-poverty tracts might theoretically overstate the effectiveness of the program. However, the lack of freedom in selecting an eligible community's boundaries, which arguably is contrary to the stated goals of local decision-making and autonomy could impact the efficiency of the development and execution of any strategic plan and make it more difficult to take advantage of agglomeration economies. Future research on the long-term impact of this program could include a more detailed understanding of how the decisions over EC boundaries were made, in addition to examining the impact of geographic size, community contiguousness, and the use of existing political boundaries on relevant economic outcomes.

Lastly, a closer examination of the economic impact of spending in rural areas reveals that, although programs like the EZ/EC do allow communities to develop plans that are specific to their location, many "traditional" programs which are frequently used in urban areas are not necessarily appropriate for rural communities (Hyman, 1998; Deavers et al., 1986). Kilkenny (2010) outlines the difficulty of program design and program evaluation for rural communities while pointing out the incoherence of current economic theory surrounding programs which seek to alleviate rural poverty and promote economic development. She notes transportation infrastructure spending in rural counties tends to promote urbanization of populations rather than rural development, although many Enterprise Communities focused efforts not on improving roads, but improving access to public transportation that allowed for increased mobility to jobs around the region (USDA, 2001). Additionally, job training programs can frustrate workers who cannot find local jobs and can result in such higher human capital workers emigrating to urban locations and construction of low-income housing may actually decrease mobility for the poor by discouraging them to move to locations where they may have better opportunities Kilkenny (2010). In one case, the community is worse off for losing the newly skilled worker and in the other case, the low-income family may be worse off by remaining in the community. Elements of both types of programs frequently appeared in the strategic plans of the Enterprise Communities (USDA, 2001). Glaeser and Gottlieb (2008) provides further evidence a national place-based economic policy is just as likely to do more harm than good. Thus, spatially-targeted policies which may improve the overall economic status of communities may not be the most beneficial policies for individual inhabitants or vice versa.

In this paper, I propose a variety of possible control groups to identify the impact of being awarded rural Round 1 Enterprise Community designation. I find increases in housing values compared to communities which were unsuccessful in their applications, but little evidence of unemployment or poverty differences between those groups or control groups identified through matching procedures. Identifying the efficacy of these programs is not just important in retrospect, but also because such programs continue to be implemented. For example, Congress implemented the Gulf Opportunity Zones over wide swaths of Louisiana, southern Mississippi and western Alabama in the wake of Hurricanes Katrina and (Stoker and Rich, 2006). I intended to continue this research by improving the identification of Champion Communities, identifying specific policies individual communities enacted to empirically identify best practices as well as utilize 2010 Census data to better evaluate the rural designees for all rounds of competition of the EZ/EC Initiative. As data availability continues to improve, it is important that researchers of evaluations of economic development programs in rural areas work to correctly identify which programs are effective in improving the economic outcomes of residents and have external validity and what policies are inefficient in their execution.

2.7 Figures and Tables

Figure 2.1: **Histogram of Ratio between 1990 Tract and County Unemployment Rates for Round 1 Enterprise Communities**

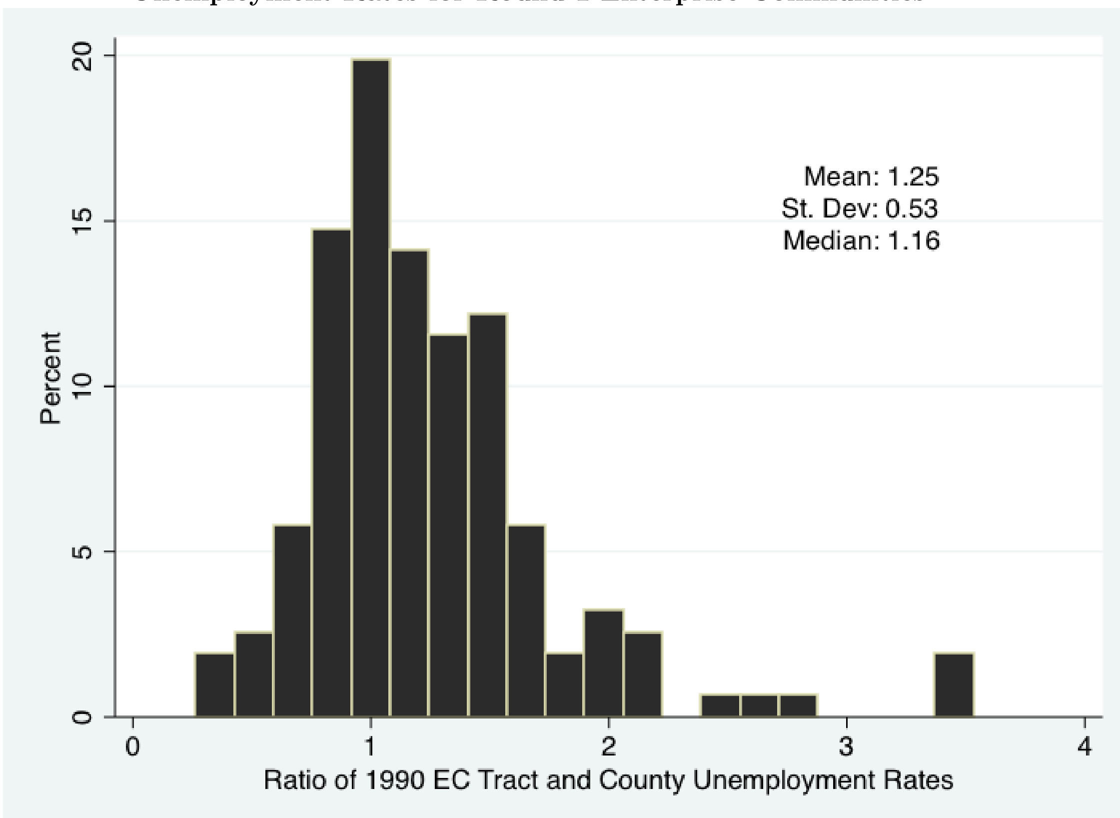


Table 2.1: **Summary 1990 statistics of Undesignated Tracts, Round 1 EC Tracts, Round 1 CC Tracts, Tracts Bordering Round 1 EC Tracts and Rounds 2 and 3 EZ, EC and RC Tracts**

	Undesignated	R1 EC	R1 CC	R1 EC Border	Round 2&3 EZ/EC/RC
1990 Total Population	3826.4	3870.0	3839.8	3965.8	3475.5
	(1734.1)	(1702.3)	(1553.4)	(1635.9)	(1655.0)
1990 Median Housing Values	88190.7	38423.9	36311.7	50693.0	37370.2
	(82311.6)	(18911.3)	(20321.7)	(40067.6)	(34156.4)
1990 Unemployment Rate	0.0687	0.137	0.121	0.0870	0.140
	(0.0534)	(0.0697)	(0.0457)	(0.0417)	(0.0697)
1990 Median Family Income	32943.6	18933.2	18586.5	25086.4	18049.2
	(18108.0)	(7628.8)	(7179.5)	(9197.7)	(8939.5)
1990 Poverty Rate	0.135	0.361	0.352	0.225	0.361
	(0.124)	(0.0972)	(0.0992)	(0.0899)	(0.122)
1990 Child (> 18) Poverty Rate	0.173	0.469	0.433	0.291	0.452
	(0.165)	(0.126)	(0.126)	(0.122)	(0.146)
1990 HS Dropout Rate	0.115	0.164	0.167	0.133	0.161
	(0.108)	(0.0929)	(0.103)	(0.0815)	(0.0951)
1990 Prop. 25+ with no HS deg.	0.253	0.494	0.454	0.406	0.451
	(0.149)	(0.108)	(0.131)	(0.122)	(0.123)
1990 Occ. Concentration Index	1586.7	1526.5	1495.8	1467.8	1498.7
	(421.6)	(342.4)	(235.9)	(240.8)	(335.4)
1988 Pay Per Employee	19.91	14.45	15.12	15.10	14.58
	(4.054)	(2.501)	(3.526)	(2.861)	(2.897)
1990 Pay Per Employee	21.21	15.16	16.03	15.94	15.55
	(4.373)	(2.518)	(3.730)	(2.956)	(3.286)
1992 Pay Per Employee	23.14	16.70	17.52	17.50	16.94
	(4.863)	(2.539)	(3.808)	(3.051)	(3.311)
1990 Welfare Assistance Rate	0.0791	0.205	0.171	0.126	0.195
	(0.0821)	(0.0730)	(0.0705)	(0.0563)	(0.0883)
1990 Prop. Black	0.121	0.369	0.235	0.214	0.248
	(0.230)	(0.311)	(0.286)	(0.234)	(0.303)
1990 Prop. White	0.805	0.578	0.711	0.723	0.612
	(0.256)	(0.294)	(0.275)	(0.235)	(0.321)
1990 Prop. Hisp./Latino	0.0809	0.0980	0.120	0.0814	0.0940
	(0.158)	(0.265)	(0.259)	(0.215)	(0.243)
1990 Prop. 25+ with BA	0.198	0.0754	0.0999	0.100	0.0920
	(0.149)	(0.0359)	(0.0997)	(0.0649)	(0.0531)
1990 Elderly Poverty Rate	0.127	0.338	0.305	0.254	0.338
	(0.112)	(0.131)	(0.124)	(0.116)	(0.153)
1990 Population Density	5078.1	617.5	823.2	307.2	642.6
	(11592.2)	(1361.0)	(1786.7)	(1097.8)	(1832.9)
1990 Prop. >65y	0.129	0.141	0.130	0.138	0.132
	(0.0737)	(0.0395)	(0.0509)	(0.0482)	(0.0500)
1990 Prop. Child <18y	0.254	0.311	0.288	0.283	0.312
	(0.0699)	(0.0439)	(0.0707)	(0.0426)	(0.0639)
Observations	64176	156	506	302	360

Note: Undesignated tracts included tracts not otherwise included in another column from states that included an Enterprise Community. See Appendix for listing.
Mean of each variable with standard deviation in parentheses.

Table 2.2: **2000-1990 Difference in statistics of Undesignated Tracts, Round 1 EC Tracts, Round 1 CC Tracts, Tracts Bordering Round 1 EC Tracts and Rounds 2 and 3 EZ, EC and RC Tracts**

2000-1990 Variable	Undesignated	R1 EC	R1 CC	R1 EC Border	Round 2&3 EZ/EC/RC
Unemployment Rate	**-0.00530**	-0.0251	-0.0211	**-0.00980**	-0.0254
	(0.0416)	(0.0621)	(0.0496)	(0.0411)	(0.0609)
Log Median Family Income	0.509	0.434	0.492	0.392	**0.587**
	(0.515)	(0.295)	(0.422)	(0.309)	(0.636)
Log Median Home Value	**0.526**	0.425	**0.496**	0.461	0.531
	(0.553)	(0.273)	(0.419)	(0.347)	(0.663)
OCI	219.3	188.3	223.1	225.1	245.8
	(272.4)	(263.2)	(204.5)	(246.3)	(433.1)
Log Pay Per Employee[a]	**0.342**	0.302	0.303	0.311	0.295
	(0.0848)	(0.0867)	(0.115)	(0.100)	(0.106)
Poverty Rate	**-0.00327**	-0.0709	-0.0650	**-0.0316**	-0.0662
	(0.0559)	(0.0699)	(0.0701)	(0.0614)	(0.0855)
Child Poverty Rate	**-0.008**	-0.0890	-0.0834	**-0.0360**	-0.0719
	(0.103)	(0.105)	(0.105)	(0.096)	(0.133)
Welfare Assistance Rate	**0.00572**	-0.0187	**-0.00254**	**-0.00267**	-0.0180
	(0.0423)	(0.0730)	(0.0586)	(0.0460)	(0.0698)
Hs Dropout Rate	-0.0150	-0.00895	-0.0274	-0.00725	-0.0214
	(0.111)	(0.107)	(0.106)	(0.104)	(0.114)
Proportion No HS degree	**-0.0487**	-0.0977	-0.0917	-0.0920	-0.0866
	(0.0652)	(0.0567)	(0.0584)	(0.0676)	(0.0682)
Log Population	**0.1137**	0.0225	0.0442	**0.0873**	0.0535
	(0.3300)	(0.2040)	(0.3052)	0.2568	(0.2351)
Observations	64176	156	506	302	360

[a]Difference calculated for 2004-1994.

Mean of each difference with standard deviation in parentheses.

Statistically significant difference-in-differences with Round 1 ECs at the 95% confidence level are bolded.

Table 2.3: **Effect of Enterprise Community Designation for 2000 OutcomesRelative to 1994 Champion Communities**

2000 Outcomes	(1) Unemp. Rate	(2) Log Median Family Inc.	(3) Log Median Housing Val.	(4) OCI	(5) Log Payroll Per Emp. 2004	(6) Log Pop.
EC designation (vs. any R1 CC)	0.00378 (0.00369)	0.0252 (0.0171)	0.0441** (0.0200)	-0.736 (22.88)	0.0120 (0.00921)	-0.0141 (0.0295)
Observations	771	771	768	771	771	771
R-squared	0.353	0.546	0.648	0.345	0.691	0.78
EC designation (vs. only R1 CC)	0.00513 (0.00379)	0.0279 (0.0177)	0.0382* (0.0205)	-7.453 (24.29)	0.00788 (0.00956)	0.0200 (0.0255)
Observations	658	658	656	658	658	657
R-squared	0.346	0.536	0.660	0.366	0.680	0.77

2000 Outcomes	(7) Poverty Rate	(8) Child Pov. Rate	(9) Gov't Asst. Rate	(10) HS Dropout Rate	(11) Prop. No HS Degree
EC designation (vs. any R1 CC)	-0.00466 (0.00566)	-0.0142* (0.00836)	-0.00317 (0.00456)	0.00173 (0.00756)	-0.00211 (0.00494)
Observations	771	771	771	771	771
R-squared	0.657	0.529	0.574	0.224	0.815
EC designation (vs. only R1 CC)	-0.00368 (0.00580)	-0.0129 (0.00859)	-0.00285 (0.00474)	0.00153 (0.00761)	0.00007 (0.00498)
Observations	658	658	658	658	658
R-squared	0.668	0.534	0.570	0.249	0.826

Complete set of 1990 controls listed in the Appendix.Full results available upon request.
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.4: **Effect of Enterprise Community Designation for 2000 Outcomes Relative to Only 1994 and Future Designated Communities**

2000 Outcomes	(1) Unemployment Rate	(2) Log Median Family Inc.	(3) Log Median Housing Val.	(4) OCI	(5) Log Payroll Per Emp. 2004	(6) Log Pop.
EC designation	0.00165	0.0163	0.0376*	9.679	0.0180**	-0.0228
	(0.00369)	(0.0153)	(0.0202)	(23.75)	(0.00891)	(0.02111)
Observations	1,311	1,311	1,306	1,311	1,311	1,311
R-squared	0.438	0.602	0.695	0.372	0.667	0.847

2000 Outcomes	(7) Poverty Rate	(8) Child Pov. Rate	(9) Gov't Asst. Rate	(10) HS Dropout Rate	(11) Prop. No HS Degree
EC designation	-0.00360	-0.0111	0.000683	0.00322	0.000427
	(0.00551)	(0.00802)	(0.00445)	(0.00718)	(0.00484)
Observations	1,311	1,311	1,311	1,311	1,311
R-squared	0.671	0.561	0.566	0.176	0.795

Complete set of 1990 controls listed in the Appendix. Full results available upon request.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: **Effect of Enterprise Community Designation for 2000 OutcomesRelative to All Tracts**

2000 Outcomes	(1) Unemployment Rate	(2) Log Median Family Inc.	(3) Log Median Housing Val.	(4) OCI	(5) Log Payroll Per Emp. 2004	(6) Log Pop.
Enterprise Community	-0.00596	0.0606***	0.0178	-91.34***	0.00646	0.0199
	(0.00371)	(0.0151)	(0.0182)	(19.62)	(0.00845)	(0.01584)
Champion Community	-0.00934***	0.0543***	-0.00121	-58.55***	-0.0127***	0.0169*
	(0.00218)	(0.0113)	(0.0120)	(12.79)	(0.00578)	(0.00949)
Surrounding EC Tract	-0.00186	0.0202**	0.0124	-33.48**	-0.00926	0.0097
	(0.00192)	(0.00870)	(0.0125)	(13.20)	(0.00611)	(0.01114)
Observations	35,555	35,519	35,407	35,555	35,554	35,545
R-squared	0.518	0.799	0.829	0.450	0.884	0.759
State Controls						
Enterprise Comm.	-0.00745**	0.0666***	0.0105	-84.91***	0.0165*	0.0254*
	(0.00360)	(0.0141)	(0.0166)	(19.07)	(0.00866)	(0.01501)
Champion Comm.	-0.00880***	0.0571***	0.0148	-53.73***	-0.000949	0.0309**
	(0.00220)	(0.0110)	(0.0112)	(12.44)	(0.00545)	(0.00934)
Surr. EC Tract	-0.00260	0.0251***	-0.00618	-26.40**	-0.00160	0.0106
	(0.00187)	(0.00843)	(0.0118)	(12.89)	(0.00607)	0.01103
Observations	35,555	35,519	35,407	35,555	35,554	35,545
R-squared	0.528	0.805	0.858	0.455	0.893	0.767

Complete set of 1990 controls listed in the Appendix. Full results available upon request.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: **Effect of Enterprise Community Designation for 2000 OutcomesRelative to All Tracts**

2000 Outcomes	(7) Poverty Rate	(8) Child Pov. Rate	(9) Gov't Asst. Rate	(10) HS Dropout Rate	(11) Prop. No HS Degree
Enterprise Comm.	-0.00960*	-0.00482	0.00410	-0.0114	0.00822*
	(0.00518)	(0.00787)	(0.00521)	(0.00807)	(0.00477)
Champion Commu.	-0.00568*	-0.00495	0.00138	-0.0256***	0.00695**
	(0.00338)	(0.00495)	(0.00237)	(0.00434)	(0.00297)
Surr. EC Tract	-0.00459	-0.000587	0.00139	-0.00691	0.00241
	(0.00299)	(0.00471)	(0.00224)	(0.00465)	(0.00338)
Observations	35,555	35,555	35,555	35,555	35,544
R-squared	0.795	0.705	0.749	0.259	0.858
State Controls					
Enterprise Community	-0.0120**	-0.00861	0.00214	-0.00707	0.00659
	(0.00500)	(0.00750)	(0.00487)	(0.00819)	(0.00464)
Champion Community	-0.00545	-0.00718	0.000728	-0.0204***	0.00992***
	(0.00333)	(0.00480)	(0.00221)	(0.00437)	(0.00290)
Surrounding EC Tract	-0.00655**	-0.00466	0.000528	-0.00576	0.00295
	(0.00293)	(0.00459)	(0.00209)	(0.00469)	(0.00311)
Observations	35,555	35,555	35,555	35,555	35,544
R-squared	0.798	0.710	0.759	0.280	0.862

Complete set of 1990 controls listed in the Appendix. Full results available upon request.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7: **Logit Regression for Propensity Score Estimation**

VARIABLES	Logit	Odds ratio
log 1990 Tract Population	0.491**	1.633**
	(0.204)	(0.333)
log Tract Area	0.383***	1.467***
	(0.0621)	(0.0911)
1990 Unemployment Rate	2.935	18.82
	(1.909)	(35.92)
1990 Poverty Rate	10.47***	35,367***
	(2.521)	(89,171)
1990 HS Dropout Rate	0.0692	1.072
	(0.965)	(1.034)
log 1990 Median Home Value	-0.246	0.782
	(0.281)	(0.220)
log 1990 Median Fam. Income	0.465	1.592
	(0.381)	(0.607)
1990 Car Ownership Rate	3.639**	38.06**
	(1.525)	(58.04)
1990 Prop. 25+ with BA	3.739	42.04
	(2.431)	(102.2)
1990 Prop. 25+ with HS degree	-5.509***	0.00405***
	(1.333)	(0.00540)
1990 Occupational Concentration Index	-0.00108***	0.999***
	(0.000364)	(0.000364)
1990 Prop. < 50per of Poverty Line	-8.326***	0.000242***
	(2.472)	(0.000599)
1990 Prop. > 200per of Poverty Line	-4.387**	0.0124**
	(1.932)	(0.0240)
1990 Prop. Black	6.369***	583.2***
	(1.055)	(615.4)
1990 Prop. White	5.074***	159.8***
	(1.089)	(174.1)
1990 Prop. Hisp./Latino	3.266***	26.20***
	(0.697)	(18.26)
1990 Welfare Assistance Rate	3.604**	36.74**
	(1.795)	(65.96)
Log 1992 Pay Per Employee	-3.281***	0.0376***
	(0.559)	(0.0210)
Change in Pay Per Employee Growth 88-92	0.392	1.480
	(0.646)	(0.956)
Constant	-7.206	0.000742
	(4.462)	(0.00331)
Observations	34,983	

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.8: **Nearest Neighbor Matching Bias Reduction Evaluation**

1990 Variable	Sample	Mean Treated	Mean Control	%bias	%reduct bias	t-stat	t-test p-value
Log Population	Unmatched	8.148	8.154	-1.2		-0.14	0.89
	Matched	8.151	8.162	-2.1	-82.5	-0.19	0.85
Log Tract Area	Unmatched	3.713	1.338	120.0		14.43	0.00
	Matched	3.719	3.620	5.0	95.8	0.41	0.68
Unemployment Rate	Unmatched	0.137	0.069	111.6		16.77	0.00
	Matched	0.136	0.129	12.5	88.8	0.93	0.35
Poverty Rate	Unmatched	0.361	0.139	207.0		23.74	0.00
	Matched	0.361	0.357	3.6	98.3	0.28	0.78
High School Dropout Rate	Unmatched	0.164	0.122	41.7		4.91	0.00
	Matched	0.163	0.158	5.2	87.5	0.49	0.63
Log Median Housing Value	Unmatched	10.47	11.03	-93.1		-9.34	0.00
	Matched	10.47	10.52	-8.2	91.1	-1.05	0.29
Log Median Family Income	Unmatched	9.784	10.189	-82.9		-8.55	0.00
	Matched	9.785	9.809	-4.8	94.2	-0.55	0.59
Car Ownership Rate	Unmatched	0.808	0.900	-88.4		-10.19	0.00
	Matched	0.808	0.815	-6.7	92.4	-0.55	0.59
Percent with College Degree	Unmatched	0.075	0.188	-107.4		-9.77	0.00
	Matched	0.076	0.079	-3.4	96.9	-0.78	0.44
Percent with HS Degree	Unmatched	0.506	0.736	-177.0		-19.24	0.00
	Matched	0.508	0.507	0.6	99.7	0.07	0.95
Occupational Concen. Index	Unmatched	1526.5	1559.3	-10.1		-1.35	0.18
	Matched	1526.7	1527.2	-0.2	98.3	-0.02	0.99
Percent with Inc. below 50% Pov.	Unmatched	0.159	0.061	144.1		18.91	0.00
	Matched	0.159	0.158	0.7	99.5	0.05	0.96
Percent with Inc. above 200% Pov.	Unmatched	0.358	0.673	-212.6		-21.40	0.00
	Matched	0.359	0.353	4.1	98.1	0.48	0.63
Percent Black	Unmatched	0.369	0.128	87.9		13.00	0.00
	Matched	0.371	0.401	-10.9	87.6	-0.79	0.43
Percent White	Unmatched	0.578	0.800	-81.3		-11.04	0.00
	Matched	0.575	0.556	7.1	91.3	0.54	0.59
Percent Hispanic	Unmatched	0.098	0.072	12.0		2.17	0.03
	Matched	0.092	0.079	6.0	49.7	0.50	0.62
Gov't Assistance Rate	Unmatched	0.205	0.083	162.8		19.76	0.00
	Matched	0.206	0.195	14.4	91.2	1.10	0.27
Log Payroll Per Employee 1992	Unmatched	2.804	3.097	-162.5		-17.93	0.00
	Matched	2.804	2.802	1.2	99.3	0.10	0.92
1988-1992 Diff. in Δ Pay Per Emp.	Unmatched	0.053	0.027	29.2		4.49	0.00
	Matched	0.054	0.074	-23.0	21.0	-1.21	0.23

Sample	Pseudo R^2	χ^2	$p>\chi^2$
Unmatched	0.426	850.63	0.00
Matched	0.04	17.29	0.57

Table 2.9: **Nearest Neighbor Matching Propensity Score Comparison**

2000 Outcome	Sample	Mean Treated	Mean Controls	Difference	S.E.	T-stat
Log Population	Unmatched	8.171	8.278	-0.107	0.043	-2.49
	ATT	8.162	8.192	-0.030	0.051	-0.59
Unemployment	Unmatched	0.112	0.064	0.048	0.004	11.57
Rate	ATT	0.111	0.105	0.005	0.007	0.77
Log Median	Unmatched	10.22	10.73	-0.516	0.033	-15.60
Family Income	ATT	10.22	10.20	0.024	0.033	0.74
Log Median	Unmatched	10.89	11.61	-0.721	0.049	-14.72
Housing Value	ATT	10.89	10.91	-0.021	0.046	-0.46
Occupational	Unmatched	1714.8	1790.6	-75.8	28.4	-2.67
Concen. Index	ATT	1715.8	1788.5	**-72.8**	36.7	-1.98
Payroll per	Unmatched	3.182	3.494	-0.312	0.018	-16.92
Employee (2004)	ATT	3.181	3.197	-0.015	0.024	-0.64
Poverty Rate	Unmatched	0.290	0.136	0.155	0.009	17.69
	ATT	0.290	0.297	-0.007	0.014	-0.51
Child Poverty	Unmatched	0.380	0.174	0.207	0.012	17.39
Rate	ATT	0.380	0.380	0.000	0.018	-0.02
Gov't Assistance	Unmatched	0.186	0.087	0.099	0.006	16.79
Rate	ATT	0.186	0.175	0.012	0.010	1.15
HS Dropout	Unmatched	0.155	0.105	0.050	0.008	6.06
Rate	ATT	0.155	0.156	-0.001	0.012	-0.09
Percent Without	Unmatched	0.603	0.787	-0.184	0.011	-16.77
HS Degree	ATT	0.605	0.614	-0.009	0.013	-0.68

Observations	Off Support	On Support	TOTAL
Untreated	0	34,681	34,681
Treated	1	155	156
Total	1	34,836	34,837

Table 2.10: **Radius Matching Bias Reduction Evaluation**

1990 Variable	Sample	Mean Treated	Mean Control	%bias	%reduct bias	t-stat	t-test p-value
Log Population	Unmatched	8.148	8.154	-1.2		-0.14	0.89
	Matched	8.148	8.159	-2.0	-75.2	-0.18	0.86
Log Tract Area	Unmatched	3.713	1.338	120.0		14.43	0.00
	Matched	3.717	3.416	15.2	87.3	1.16	0.25
Unemployment Rate	Unmatched	0.137	0.069	111.6		16.77	0.00
	Matched	0.131	0.127	7.5	93.3	0.52	0.60
Poverty Rate	Unmatched	0.361	0.139	207.0		23.74	0.00
	Matched	0.355	0.333	20.2	90.2	1.39	0.17
High School Dropout Rate	Unmatched	0.164	0.122	41.7		4.91	0.00
	Matched	0.163	0.157	6.0	85.7	0.53	0.60
Log Median Housing Value	Unmatched	10.47	11.03	-93.1		-9.34	0.00
	Matched	10.48	10.54	-10.2	89.1	-1.09	0.28
Log Median Family Income	Unmatched	9.784	10.189	-82.9		-8.55	0.00
	Matched	9.804	9.835	-6.3	92.4	-0.64	0.52
Car Ownership Rate	Unmatched	0.808	0.900	-88.4		-10.19	0.00
	Matched	0.808	0.820	-11.6	86.8	-0.86	0.39
Percent with College Degree	Unmatched	0.075	0.188	-107.4		-9.77	0.00
	Matched	0.077	0.093	-15.2	85.8	-2.11	0.04
Percent with HS Degree	Unmatched	0.506	0.736	-177.0		-19.24	0.00
	Matched	0.513	0.539	-20.2	88.6	-1.80	0.07
Occupational Concen. Index	Unmatched	1526.5	1559.3	-10.1		-1.35	0.18
	Matched	1523.2	1539.7	-5.1	49.7	-0.44	0.66
Percent with Inc. below 50% Pov.	Unmatched	0.159	0.061	144.1		18.91	0.00
	Matched	0.155	0.147	12.9	91.0	0.88	0.38
Percent with Inc. above 200% Pov.	Unmatched	0.358	0.673	-212.6		-21.40	0.00
	Matched	0.366	0.401	-23.2	89.1	-2.02	0.05
Percent Black	Unmatched	0.369	0.128	87.9		13.00	0.00
	Matched	0.369	0.356	4.8	94.6	0.34	0.73
Percent White	Unmatched	0.578	0.800	-81.3		-11.04	0.00
	Matched	0.578	0.594	-6.0	92.6	-0.45	0.65
Percent Hispanic	Unmatched	0.098	0.072	12.0		2.17	0.03
	Matched	0.085	0.073	5.9	51.1	0.50	0.62
Gov't Assistance Rate	Unmatched	0.205	0.083	162.8		19.76	0.00
	Matched	0.202	0.188	19.0	88.3	1.26	0.21
Log Payroll Per Employee 1992	Unmatched	2.804	3.097	-162.5		-17.93	0.00
	Matched	2.812	2.846	-18.8	88.5	-1.42	0.16
1988-1992 Diff. in Δ Pay Per Emp.	Unmatched	0.053	0.027	29.2		4.49	0.00
	Matched	0.053	0.059	-6.6	77.3	-0.37	0.72

Sample	Pseudo R^2	χ^2	$p>\chi^2$
Unmatched	0.426	850.63	0.00
Matched	0.025	10.12	0.95

Table 2.11: **Radius Matching Propensity Score Comparison**

2000 Outcome	Sample	Mean Treated	Mean Controls	Difference	S.E.	T-stat
Log Population	Unmatched	8.171	8.278	-0.107	0.043	-2.49
	ATT	8.169	8.208	-0.038	0.051	-0.76
Unemployment	Unmatched	0.112	0.064	0.048	0.004	11.57
Rate	ATT	0.109	0.104	0.006	0.004	1.26
Log Median	Unmatched	10.22	10.73	-0.516	0.033	-15.60
Family Income	ATT	10.23	10.28	**-0.050**	0.026	-1.96
Log Median	Unmatched	10.89	11.61	-0.721	0.049	-14.72
Housing Value	ATT	10.90	11.01	**-0.114**	0.042	-2.69
Occupational	Unmatched	1714.8	1790.6	-75.8	28.4	-2.67
Concen. Index	ATT	1710.6	1780.8	**-70.2**	28.9	-2.43
Payroll per	Unmatched	3.182	3.494	-0.312	0.018	-16.92
Employee (2004)	ATT	3.187	3.241	**-0.054**	0.017	-3.23
Poverty	Unmatched	0.290	0.136	0.155	0.009	17.69
Rate	ATT	0.286	0.273	0.013	0.009	1.48
Child Poverty	Unmatched	0.380	0.174	0.207	0.012	17.39
Rate	ATT	0.376	0.352	0.023	0.012	1.93
Gov't Assistance	Unmatched	0.186	0.087	0.099	0.006	16.79
Rate	ATT	0.184	0.168	**0.017**	0.007	2.56
HS Dropout	Unmatched	0.155	0.105	0.050	0.008	6.06
Rate	ATT	0.154	0.143	0.011	0.009	1.14
Percent With	Unmatched	0.603	0.787	-0.184	0.011	-16.77
HS Degree	ATT	0.609	0.640	**-0.030**	0.010	-2.96

Observations	Off Support	On Support	TOTAL
Untreated	0	34,681	34,681
Treated	9	147	156
Total	9	34,828	34,837

Table 2.12: **Summary statistics for "Matched" County Comparison**

	"Matched" Counties	EC "Counties"	Difference	P-value
Population	13512.5	45522.3	-32009.8***	0.000
	(11322.1)	(25675.9)	(4167.4)	
Avg. Housing Value	39711.3	59339.1	-19627.8**	0.001
	(6360.8)	(40910.4)	(5877.3)	
Unemployment Rate	0.0972	0.0914	0.00584	0.407
	(0.0317)	(0.0280)	(0.00701)	
Avg. Family Income	24845.9	29714.7	-4868.8***	0.000
	(2740.4)	(4769.7)	(838.3)	
Poverty Rate	0.348	0.231	0.117***	0.000
	(0.0426)	(0.0610)	(0.0116)	
Child Poverty Rate	0.452	0.304	0.147***	0.000
	(0.0623)	(0.0754)	(0.0156)	
Elderly Poverty Rate	0.334	0.246	0.0880***	0.000
	(0.0651)	(0.0919)	(0.0176)	
HS Dropout Rate	0.114	0.139	-0.0251*	0.035
	(0.0522)	(0.0473)	(0.0117)	
Prop. 25+ with no HS degree	0.449	0.407	0.0415**	0.010
	(0.0608)	(0.0779)	(0.0156)	
OCI	1365.3	1304.2	61.15*	0.019
	(123.0)	(85.18)	(25.52)	
Gov't Assistance Rate	0.167	0.128	0.0396***	0.000
	(0.0460)	(0.0361)	(0.00983)	
Percent Black	0.287	0.193	0.0936	0.102
	(0.270)	(0.198)	(0.0567)	
Percent White	0.648	0.732	-0.0835	0.085
	(0.217)	(0.190)	(0.0479)	
Percent Hispanic	0.195	0.101	0.0932	0.143
	(0.299)	(0.222)	(0.0630)	
1990 Prop. 25+ with BA	0.101	0.102	-0.000648	0.940
	(0.0394)	(0.0324)	(0.00854)	
Population Density	23.39	69.14	-45.76	0.064
	(21.48)	(170.7)	(24.36)	
Percent Elderly	0.155	0.137	0.0173*	0.022
	(0.0323)	(0.0319)	(0.00743)	
Percent Children	0.299	0.285	0.0137	0.067
	(0.0328)	(0.0305)	(0.00739)	
Observations	50	30		

See text for column definitions.

Mean of each variable with standard deviation in parentheses.

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

Table 2.13: **Effect of Enterprise Community Designation for 2000 OutcomesRelative to "Matched" Counties**

VARIABLES	(1) Unemployment Rate	(2) HS Dropout Rate	(3) No HS Degree	(4) OCI	(5) Log Population
Combined Enterprise Community	0.00651	0.0270	0.00829	-97.12**	-0.0095
	(0.00865)	(0.0199)	(0.0111)	(45.29)	(0.0421)
Observations	80	80	80	80	80
R-squared	0.647	0.388	0.907	0.579	0.994
VARIABLES	(5) Log Avg. Housing Value	(6) Poverty Rate	(7) Log Avg Family Inc.	(8) Child Poverty Rate	(9) Gov't Asst. Rate
Combined Enterprise Community	0.00818	0.00408	-0.0279	0.0134	-0.00179
	(0.0581)	(0.0138)	(0.0288)	(0.0193)	(0.0132)
Observations	80	80	80	80	80
R-squared	0.903	0.833	0.850	0.820	0.659

Complete set of 1990 controls listed in the Appendix. Full results available upon request.
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.14: **Effect of Funding Levels on 2000 Enterprise Community Outcomes**

VARIABLES	(1) Unemployment Rate	(2) HS Dropout Rate	(3) No HS Degree	(4) OCI	(5) Log Population
Log Total Funding 2001	0.00359	-0.0110	0.00666	43.80**	0.0139
	(0.00445)	(0.00722)	(0.00694)	(14.05)	(0.02289)
Observations	30	30	30	30	30
R-squared	0.856	0.900	0.963	0.961	0.997
VARIABLES	(6) Log Avg. Housing Value	(7) Poverty Rate	(8) Log Avg Family Inc.	(9) Child Poverty Rate	(10) Gov't Asst. Rate
Log Total Funding 2001	0.0643**	0.0110**	-0.00335	0.0172**	-0.000183
	(0.0233)	(0.00478)	(0.0105)	(0.00680)	(0.00536)
Observations	30	30	30	30	30
R-squared	0.985	0.955	0.974	0.959	0.916

Complete set of 1990 controls listed in the Appendix. Full results available upon request.
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

CHAPTER III

Pump Pressure: Income, Public Transportation and the Time Use Response to Gas Prices

3.1 Introduction

The economic value that urban transit systems generate are the result of economies of scale from both the manufacture and provision of transportation as well as the increased ease of labor mobility within a region and potentially reducing environmentally harmful emissions. Transit expansion has also been shown to contribute both to migration of low income individuals towards such areas as well as economic development and property value increases in newly serviced neighborhoods (Glaeser et al., 2008; Bowes and Ihlanfeldt, 2001; Gibbons and Machin, 2005; Hess and Almeida, 2007). Public provision and support of transit systems are justified by policy makers based on these arguments as private enterprises are not be able to generate the economies of scale to see low enough average costs for sustainability and profit maximization are not likely to lead to pricing and market targeting decisions that generate as much of the desired externalities.

In addition, fuel taxes are implemented by policy makers for both the reason of reducing driving to reduce emissions as well as to provide general revenue. This tax revenue is frequently earmarked to provide funding for highways and roads or it can contribute to the support of other forms of transportation. Utilization of funds towards highways frames the gasoline tax as a “use” tax instead of a Pigouvian tax that is attempting to capture the cost of the negative externality of the emissions. Indeed, maintaining and expanding the road system through gasoline tax revenues will reduce the efficacy of such a tax as a means to reduce driving.

Besides potential connections through funding, there is another economic interplay between these two transportation policy spheres. Increasing the efficacy, scope and speed of a public transportation system should induce increased ridership. It is unclear, however, how such an event would change the incidence and effect of a subsequent change in gasoline prices as a result of an increase in gasoline taxes (or market forces, for that matter.) One prediction would be that the relatively attractive mass transit system could generate greater levels of substitution when higher gas prices occur. This would strengthen any marginal effects of gas taxes on reducing driving behavior. On the other hand, the relatively more attractive system may have already induced substitution for gas price elastic travelers, regardless of the current gas prices. That is, the elasticity of car travel with respect to gas prices may be much lower in areas with more attractive public transportation systems. Those who continue to drive do because of their needs or tastes. In addition, better public transportation may attract residents who are highly elastic with respect to driving. From a statistical standpoint, this would increase the average elasticity in these cities, but further separate the difference in elasticity in times of low gas prices and times of high gas prices. Separately, roads travelled by those who switched to public transportation could become more attractive during the new equilibrium transition, resulting in little to no change in overall driving as new driving trips emerge.

Thus, the theoretical question of whether an increase in public transportation capacity/efficacy dampens or heightens the effect of gas prices on car travel is ambiguous. This is an interesting empirical question to examine because a larger effect of gas prices strengthens a policy case towards higher gas prices on environmental grounds as reduced usage leads to lower carbon emissions. A lower effect of gas prices weakens such a case and implies only higher revenues. This may be desirable as a funding option, but does not reduce emissions. Indeed Parry and Small (2009) find that while public transportation funding is efficiency improving overall, it is very much a second-best solution to gasoline taxes in the reducing the externalities of automobiles. The advent of more fuel-efficient automobile technology does help, but fossil-fuel based sources of gasoline and electricity are still projected to be standard for decades to come. In the realm of public transportation policy, if funding for public transportation expansion is linked to higher gas taxes, but higher gas prices are leading to increasingly inelastic usages of car travel that, for practical or preference based reasons are not substituted towards public transportation, then this could be viewed as an unfair policy. Taste based reasons for driving can be important, and if gas taxes are perceived as a form of use tax, earmarking associated revenue for alternative transportation modes could be politically unpopular. Further, low income drivers may not have access to the public transportation system where they live or work and lack the ability to change the locations of either.

In this paper, I find that the interaction effect of public transportation actually dampens the effect of gas prices reducing car travel, primarily through reduced leisure-purposed travel with no evidence of an interaction effect on work-based travel. Public transportation increases the effect of gas prices on car travel time for those making between \$75,000 and \$100,000, reversing a trend seen for other income groups. In addition, public transportation availability dramatically increases the effect of gas prices on public transportation travel time for those in the lowest income group. These results suggest that there is significant interplay between public transportation availability and policies which affect gas prices that results in behavioral changes which can differ significantly for different segments of the population.

3.2 Previous Research

Many researchers have examined the elasticity of demand for gasoline in the United States, with data being generally being culled from household expenditure surveys like the US Consumer Expenditure Survey or through consumption interviews. Meta-analysis of US based surveys show an average estimate of slightly above -0.5 (Dahl and Sterner, 1991; Espey, 1996) with short-run elasticities of demand historically between -0.2 and -0.4 (Hughes et al., 2008; Puller and Greening, 1999; Espey, 1998). Espey (1998) also found that elasticity estimates were falling in more recent years and Hughes et al. (2008) found a short-run elasticity that was much smaller around -0.05 using data from the early 2000s. If demand for gasoline has become more inelastic over time, it is worth investigating how a predicted increased income effect would manifest itself in other household decisions concerning expenditures and time use behavior. More recently, Ferdous et al. (2010) expanded the use of Consumer Expenditure Survey (CES) data to model household expenditure responses to exogenous increases in transportation expenses. They found reductions in food, savings and expenditures in automobile and home-based durable goods and related maintenance.

Identifying the distributional impact of increased gas prices due to taxation or market forces is also useful to determine the relative regressivity of tax changes. Inelastic demand may result in gas price increases having a larger impact on low-income households as a percentage of income, but several papers have noted that increases in gas prices such as via a tax are not actually as regressive as expected. Higher-income households drive much more than lower-income households (Poterba, 1991; West, 2004), however whether a change is regressive or not depends on if you use a definition based on total welfare impact or as a proportion of income or wealth. Bento et al. (2009) and Nicol (2003) also estimate differential effects of changes in gas prices or taxes on different subgroups. Schmalensee and Stoker (1999) determined there to be an income elasticity of gasoline close to zero at lower incomes, suggesting a "subsistence" level of gasoline consumption. This paper provides further evidence of such a hypothesis and may provide further evidence as to what income levels generate demand for gasoline consumption above subsistence level.

The analysis of public transportation subsides by Parry and Small (2009) suggest they are efficiency increasing, although they do not address distributional aspect of the welfare gains. Haire and Machemehl (2007) examined cross-price elasticities of various forms of public transportation for five cities and calculated an average elasticity of .24, although estimates for individual modes and cities varied widely. Conversely, Winston and Maheshri (2006) argues every transit system reduces overall welfare except for San Francisco's BART. While I do not comment on the overall welfare improving qualities of existing transit systems, I do provide new evidence on how different income groups are utilizing public transportation and the extent to which it is used as an alternative when adjusting to rising gas prices using national data.

While there is a large literature examining the macroeconomic impact of oil and gasoline prices on economic growth and demand, there has been less research attempting to estimate the impact of gas prices on individual behavior outside of automotive and gasoline purchases. Edelstein and Kilian (2009) examine consumption shifts due to changes in energy prices, suggesting they are magnified by higher savings rates caused by consumer pessimism on top of the negative shock to discretionary income. Gicheva et al. (2007), looking at CES and retail-level data in California found little decline in gasoline consumption itself; they found elasticities of expenditures on food-away-from-home indicating a substitution on food consumption based on an income effect. Additionally, grocery purchases were more likely to be made on on-sale items when gasoline prices rose. Similar research by Courtemanche (2009) linked obesity rates with decreased gas prices, estimating a permanent one dollar increase in gasoline prices could reduce obesity by as much as 10% through increased exercise and a reduced number meals eaten outside the home.

The use of time use data has not been fully exploited, particularly in the United States where the BLS has only maintained a yearly survey since 2003, and there is a call to implement the data in general in economics as well as in transportation research (Hamermesh et al., 2005; Hamermesh, 2009; Pendyala and Goulias, 2002; Bhat and Koppelman, 1999; Michelson, 2005; Joyce and Stewart, 1999). That said, there is some suggestion time use data is limited in its usability in the U.S. as data are limited to one individual in a household with no consumption data and time duration/participation rates may not provide adequate measures as to the relative utility of any of the activities chosen by a respondent (Pollack, 1999; Juster, 2009). These objections can be also be made of consumption data, but there is incredible value in approaching policy analysis using a dimension of human choice and behavior that has been generally ignored in economic research.

3.3 A Model of Time Use and Transportation

The modeling of consumer behavior to include a time budget was first popularized by Becker (1965). Along with Lancaster (1966), they introduced the idea of a utility function maximizing not over solely goods, but over "commodities" or "activities", which are functional combinations of the properties of consumer goods and/or the time spent with those goods. These commodities each have a cost in terms of the prices of the goods involved and the time allocated towards them. Individuals or households maximize their utility subject to a monetary budget and the natural limit of hours in the day. These themes were quickly picked up and refined by forcing minimum time lengths, modeling in travel behavior or allowing for monetary savings (DeSerpa, 1971; Oort, 1969; Small and Verhoef, 2007).

The model[1] which underlies the empirical analysis is based on maximizing utility utilizing a dual budget line with each activity requiring both a financial outlay to pay for the goods and services necessary and a time budget line. In addition, activities outside the home have a travel requirement which necessitates additional monetary and temporal costs. This travel requirement can be satisfied through various modes, each with their own financial cost per mile. There are only three such transportation technologies: via car (regardless of driver), via public transportation (bus, train, or subway) or via self-propelled means (walking or biking).

For simplicity, I assume the speed of each technology is constant, so the use of a price per mile or a price per unit of time is directly related. This then does not allow for intertemporal substitution of transportation (and their associated activities) based on relative temporal price differences. "Rush-hour" public transportation may have more frequent service or more expansive service compared to the weekend, while

[1] In addition to the above referenced papers, the model is also inspired by Johnson (1966) and Evans (1972).

congestion on roads are likely different during the same times. I comment on the impact this may have on the interpretation of the empirical estimations in Subsection 3.6.5. Suppose individual i gains utility through expenditures on goods, time spent in various activities and through location attributes generated by miles traveled. A non-separable utility function has the form of:

$$U = U(\mathbf{X}_i, \mathbf{T}_i, M_i), \tag{3.1}$$

where $\mathbf{X}_i$ is a vector of goods and services which can be purchased utilizing the price vector $\mathbf{P}$, $\mathbf{T}_i$ is a vector of time spent in various activities and M_i represents total miles traveled. Both goods and services and miles traveled enhance activity utility but come a cost of both time and money. $\mathbf{T}_i$ specifically does not include time spent traveling which is denoted by the vector's elements, t_i.

There exists two budget lines and a definition of M as a linear function of the time spent in various modes of transport. The monetary budget line is as follows:

$$I_i = \mathbf{P}\mathbf{X}_i + \sum_j c_j t_{ij}, \tag{3.2}$$

where I_i represents the individual's income and c_j represents the financial cost per unit of time spent in transportation mode j. The temporal budget line is;

$$T^o = \sum T_i + \sum_j t_j, \tag{3.3}$$

where T^o is the time endowment and T_{ik} are the time spent in individual activities. Additionally,

$$M_i = \sum_j g_j t_j, \tag{3.4}$$

where g_j is the speed of transportation mode j.

From this framework, the following first order conditions are derived:

$$\lambda = \frac{1}{p}\frac{\partial U}{\partial X} \quad \text{for each good,} \tag{3.5}$$

$$\tau = \frac{\partial U}{\partial T} \quad \text{for each time use activity,} \tag{3.6}$$

$$\mu = \frac{\partial U}{\partial M_i}, \tag{3.7}$$

and

$$\lambda c_j + \tau = \mu g_j \quad \forall j, \tag{3.8}$$

As stated above, to simplify, suppose there are just three modes of transportation, automobile (1), public transportation (2) and self-propelled means (3).

This means:

$$M = g_1 t_1 + g_2 t_2 + g_3 t_3. \tag{3.9}$$

We can differentiate this initially with respect to c_1 which, while modeled as the cost per unit of time of car travel, is strongly related to the price of gas:

$$\frac{\partial M}{\partial c_1} = g_1 \frac{\partial t_1}{\partial c_1} + g_2 \frac{\partial t_2}{\partial c_1} + g_3 \frac{\partial t_3}{\partial c_1}. \tag{3.10}$$

$\frac{\partial M}{\partial c_1}$ can be substituted out by recognizing it is the ratio of the marginal indirect utility of the cost of car transport and the marginal utility of miles. The former can be shown by virtue of the envelope theorem to be equal to $\frac{\partial V}{\partial c_1} = -\lambda t_1$, while the latter is simply μ from Equation 3.7. This can give us an expression for the change in time spent in car transport with respect to the price of said time of :

$$\frac{\partial t_1}{\partial c_1} = -\frac{\lambda t_1}{\mu g_1} - \frac{g_2}{g_1}\frac{\partial t_2}{\partial c_1} - \frac{g_3}{g_1}\frac{\partial t_3}{\partial c_1}. \tag{3.11}$$

Since g_j are in units of miles per hour, these are positive as would be the time spent in car travel. Shadow prices are also considered to be positive. If the effect of higher gas prices is weakly higher amounts of time spent in public transportation and self-travel, then it is assured that there will be a negative effect of gas prices on car travel. The possibility that the cross-price elasticity of gas on other forms of travel is negative is theoretically possible due to the income effect. If demand for car travel is sufficiently inelastic, less travel may be incurred in the other forms. Additionally, if car travel is necessary for income producing activities and higher gas prices result in an income shocks necessitating more car travel, the total effect could be positive. In that case, car-based travel of this form would be similar to a Giffen good, suggesting though that this is behaviorally unlikely.

Commuting is required for people to move from home to work. The value of such transportation is higher because it is necessary to access their income. As a result, the ratio $(\frac{\mu}{\lambda})$, which represents the monetary value per mile of transport, would be higher. This would generate smaller effects of gas prices on commuting time. It should be noted that this would be true of all transportation technologies as well.

Another reason may be preference-based; individuals might simply prefer driving or car-based travel over public transportation or biking/walking. The latter might also not be possible due to location and distance between home and their travel destinations, such as work. Lower levels of income should induce preference-based inelasticity to no longer dominate, but may induce necessity-based inelasticity. In the latter case, individuals may have exhausted all means already to substitute away from car-based travel.

Similarly, we can also derive an expression of the effect of car transport on the "efficacy" (modeled here as speed) of public transportation, g_2:

$$\frac{\partial M}{\partial g_2} = g_1 \frac{\partial t_1}{\partial g_2} + t_2 + g_2 \frac{\partial t_2}{\partial g_2} + g_3 \frac{\partial t_3}{\partial g_2}. \tag{3.12}$$

Again, $\dfrac{\partial M}{\partial g_2}$ can be substituted out by recognizing it is the ratio of the marginal indirect utility of the speed of public transportation and the marginal utility of miles (μ) . The former can be shown by virtue of the envelope theorem to be equal to $\dfrac{\partial V}{\partial g_2} = \mu t_2$, thus $\dfrac{\partial M}{\partial g_2} = t_2$. This yields:

$$\frac{\partial t_1}{\partial g_2} = -\frac{g_2}{g_1} \frac{\partial t_2}{\partial g_2} - \frac{g_3}{g_1} \frac{\partial t_3}{\partial g_2}. \tag{3.13}$$

Based on the result of the envelope theorem, there is a change of t_1 in total miles (M), but the distribution of time for each mode could still change. Time spent in car travel will not clearly fall, but it will take the opposite sign as the change in time spent in public transportation or walking. While it seems likely for public transportation to rise, it is important to recognize that miles are desired, not travel time, so less travel time in public transportation (but the same number of miles) could induce less time in public transport and even more time car transport if that extra time is allocated towards income producing activities, leading to an income effect on car travel dominating the substitution effect.

A further statistic of interest is the partial derivative of equation (11) with respect to g_2 and the partial derivative of equation (13) with respect to c_1. These expressions should be identical and represent the effect of the efficacy of a public transportation system on the the effect of gas prices on car usage. The two derivative equations are:

$$\frac{\partial^2 t_1}{\partial c_1 \partial g_2} = -\frac{\lambda}{\mu g_1} \frac{\partial t_1}{\partial g_2} - \frac{1}{g_1} \frac{\partial t_2}{\partial c_1} - \frac{g_2}{g_1} \frac{\partial^2 t_2}{\partial c_1 \partial g_2} - \frac{g_3}{g_1} \frac{\partial^2 t_3}{\partial c_1 \partial g_2}. \tag{3.14}$$

and,

$$\frac{\partial^2 t_1}{\partial c_1 \partial g_2} = -\frac{g_2}{g_1} \frac{\partial^2 t_2}{\partial c_1 \partial g_2} - \frac{g_3}{g_1} \frac{\partial^2 t_3}{\partial c_1 \partial g_2}. \tag{3.15}$$

As described above, this sign of this expression is uncertain because of two opposing factors. Increased public transportation attractiveness makes substitution towards its use more likely and thus cause magnify the negative effect of gas prices on driving. At the same time, however, higher public transportation usage could induce remaining car usage to be more inelastic causing a dampening of the effect of gas prices. Empirical analyses can lead to a better idea as to how this is actually playing out and if this effect differs for different income groups.

Additionally, equating the terms of equations (14) and (15) implies:

$$-\frac{\lambda}{\mu}\frac{\partial t_1}{\partial g_2} = \frac{\partial t_2}{\partial c_1}, \tag{3.16}$$

which can be rearranged in the following form:

$$\frac{\mu}{\lambda} = -\frac{\frac{\partial t_1}{\partial g_2}}{\frac{\partial t_2}{\partial c_1}}. \tag{3.17}$$

This provides an expression to determine the value of speed as the ratio of the effect of an increase in the speed of public transportation on car time use over the effect of higher gas prices on time spent in public transportation. The data I use in this paper do not include information about the actual speed of public transportation, or the specific cost of a unit of time in car travel for that matter, but this framework could be a useful structure to investigate the value of travel speed across different cities and populations in future research.

3.4 Data Sources and Scope

3.4.1 ATUS data

I utilize data from the American Time Use Survey (ATUS)[2], administered by the BLS, which consists of full-day diaries of respondent's activities and allocations of

[2]http://www.bls.gov/tus

time. Respondents are selected from outgoing rotations of the Current Population Survey (CPS). Each yearly sample is nationally representative and stratified by day of the week, with roughly a quarter of the sample diaries taken for Saturday and Sunday and a tenth of the sample for each weekday.

The ATUS reports each primary activity a respondent participates in during their survey day as well as the location of each activity and whom they were with. This allows me to identify not just the time spent traveling, but for what purpose and by what means. The BLS provides survey files that include the amount of total time each respondent spends in each activity, and I performed a similar aggregation per respondent to include similar values for the time spent in each location and transportation mode, as well as the number of incidences of each activity. In addition, ATUS provides a variety of demographic and household information collected at the time of the survey as well as many reported from the final month of the CPS. Respondents were matched with their CPS interviews to determine the Core Based Statistical Area (CBSA) for those living in one. My analysis will be restricted to the years 2005-2009. Activities are also combined to form estimates for travel time with a primary purpose for Work[3], Leisure[4] and Other Activities [5] BLS coders assign travel back home with a purpose related to the last activity.

At the introduction of the ATUS, researchers did examine to identify the accuracy of the data generated with regards to transportation and specifically with respect to the existing National Household Travel Survey which questions respondents solely on the trips made using a travel diary. Past research had suggested trip-based surveys such as the NHTS would under-estimate travel relative to activity-based surveys such

[3]This is time coded from ATUS category 5 - "Work & Work-Related Activities"

[4]"This includes time coded in ATUS categories 11 through 15 including "Eating & Drinking," "Socializing, Relaxing & Leisure," "Sports, Exercise & Recreation," "Religious and Spiritual Activities" & "Volunteer Activities"

[5]This is time spent in any other activity.

as ATUS since activity-diaries required respondents to account for every moment of the day (Harvey, 2003). However, Bose and Sharp (2005) found aggregate estimates from both surveys to be similar. Srinivasan and Yennamani (2010) argues this may have been due to changes in the NHTS instrument which probed for underreported travel activities. Those authors compared data from both surveys more closely and found certain demographic segments generate more trips reported per person with the ATUS survey relative to the NHTS, but others demonstrate fewer trips reported. Such differences however were not large.

3.4.2 Other data sources

I match the respondent with the monthly retail gas prices for the respondent's state reported by the Federal Highway Administration (FHA). The FHA reports this data by adding the federal and state taxes to the wholesale price collected by the Energy Information Administration (EIA). For respondents living in an identified CBSA, I use the American Community Survey (ACS) estimate of the percentage of commuters who use public transportation as a measure of the attractiveness and utilization of the local public transportation infrastructure. The estimate is the 5 year average over the time span 2005-2009. As such all respondents included in my data live in metropolitan areas of at least 100,000 residents. State-level unemployment rate is utilized as well, as reported by the BLS. Specification checks utilize Urbanized Area level measures of density, population, passenger miles traveled and public transportation operating expenses reported by the National Transportation Database of the FTA. Those data are described in more detail in that section.

3.4.3 Description of sample selection

Between the years of 2005 and 2009, ATUS collected diaries from 50,952 respondents. Excluding respondents for which state-month gas prices were unavailable from the FHA data yields 50,728 diaries[6]. Of these, 42,795 live in metropolitan areas with a reported estimate for consumer public transportation utilization and 37,128 have a reported household income. Table 3.1 shows selected summary statistics for this sample and the income bins that are used for analysis. As expected, the lowest income group is much more likely to be female, retired and without the presence of a partner in the household. Tables 3.2 and 3.3 present mean average-day[7] activity times for the weighted sample for each income bin. The five income bins are collapsed from categories reported from the CPS. Of note from Table 3.2, those making over $100,000 travel almost 140 minutes more per week than those making under $25,000, with a great deal of that coming from more commuting behavior due to being much more likely to be working. They do however travel for leisure and other activities more as well. Both leisure and other travel do not increase much with household income except for those in the highest household income bracket. Leisure time however declines with income (primarily a result of a decline in television watching), a product not just of increased work time but also increases in other time categories as well, indicating television may be an economically inferior activity.

Since these are not broken down by day of week, each of these should be regarded as the daily average over an entire week. The type of activity recorded is based on the primary activity in which the respondent reports participating.[8] As such, the

[6]44 respondents from Arizona and 11 from New Hampshire were excluded in late 2008 as well as entirety of the District of Columbia respondents.

[7]An average day is not the same as a "typical" day. It represents a daily average of weekly time use.

[8]For example, if a person is reading articles online with a laptop while also watching television, only one activity, whichever the respondent states as primary, will be recorded. Listening to the radio or music is known to be chronically underreported since the vast majority of such activity is performed as a secondary activity.

ATUS will under-report secondary activities[9]. Abraham et al. (2006) detail other issues involved with data collection for the ATUS, citing the length and burden of the survey in suggesting bias could be introduced if those who respond to the survey have time habits which differ from non-respondents. While I do not correct for that source of bias, results of any study using ATUS data should be interpreted with this in mind.

3.5 Price Elasticity of Gas

I initially check to see if the data from ATUS is comparable to data used from consumption surveys by estimating the elasticity of car-based travel (T_i) with respect to gas prices using the following equation:

$$ln(T_i) = \alpha_0 + \eta_1 ln(P_{st}) + \eta_2 A_{it} + \eta_3 P_{st} * A_{it} + \eta_4 X_i + \eta_5 U_{st} + \eta_6 D_t + \delta_t + \rho_s + \epsilon_i. \quad (3.18)$$

Here, P_{st} represents the three month moving average for the real price of gas for the state of the respondent in the month of the reported diary, A_i is the ACS-reported estimate for percentage of commuters in the respondent's MSA utilizing public transportation, X_i is a variety of individual and household characteristics, including employment and retiree status, age, age squared and educational attainment of the respondent and the presence of a partner, any children, or a child aged 5 or under in the household. U_{st} is the unemployment rate of the diary month and state of the respondent and D_t is a set of date controls for month, day of week and whether the diary day was a holiday. Year dummies are not used as they are severely auto-correlated with the price of gas.

[9] Although I am not making use of this aspect of the data, one noteworthy exception is that the ATUS interviewer will specifically ask and record secondary activities as they relate to child-care where appropriate.

Column 1 of Table 3.4 reports the elasticity for the entire sample. For all individuals, the elasticity of car-based travel time to gas prices is -0.098, which is lower than some older studies, but consistent with more recent ones which have noted a more recent shift towards inelastic behavior (Hughes et al., 2008; Davis and Killian, 2011). One important point to note is that travel time and gasoline purchases utilized by previous studies do not directly correspond to my measures and I have not included proper controls for the possibility of increased traffic congestion over this time period. I expect elasticities calculated using car travel time would be lower than those utilizing consumption as marginal trips would likely be of the kind which could be incorporated into trip chaining, or alternatively would be close to the respondent's home. Such marginal trips would likely be of the type utilizing routes that suffer from low gas mileage, particularly in the suburban and urban areas to which I had restricted the sample. These trips would thus have a lower travel time to gasoline consumption ratio than the average trip.

Splitting up the elasticity calculations by income group, however, illustrates large differences in responsiveness for different income levels. Those making between \$25,000 and \$50,000 report an elasticity near -0.1 as the total gives, but the elasticity is close to zero for those within households making below \$25,000 and those making above \$100,000. This is consistent with the theory suggesting a more inelastic demand due to the ability to afford the most-preferred mode or prior actions taken to already engage in the lowest cost means for necessary transportation due to income constraints. The remainder of households, those making between \$50,000 and \$100,000 report much higher elasticities around -0.15 and -0.18. Thus those middle-income households making between \$25,000 and \$100,000 are more likely to be making transportation decision that result in less marginal time spent in automobile use than the ends of the distribution. These results will also correspond with later findings showing that those in the lower end of the income spectrum are likely *already* utilizing the lowest cost possible travel and those in the highest income bin are the least likely to substitute transportation patterns as they are more likely to absorb price shocks.

The bottom half of the regression reports the elasticity with public transportation usage and its interaction with log gas prices. This has varying effects on the reported elasticities of the income groups, but on average public transportation usage in the metropolitan area brings car travel time elasticities closer to zero. This is primarily driven by the individuals in the \$75,000-\$100,000 household income group who also report the highest base elasticity. It could very well be the case that demand is more inelastic in areas with higher levels of public transportation if public transportation is already being utilized where possible, bring usage closer to the "subsistence" level of gasoline consumption.

3.6 Transport Behavior

To determine the effect of gas prices changes, public transportation availability/utilization and their interaction on the amount of time spent in various modes and purposes of travel, I estimate the following equation:

$$T_i = \alpha_0 + \beta_1 P_{st} + \beta_2 A_{it} + \beta_3 P_{st} * A_{it} + \beta_4 X_i + \beta_5 U_{st} + \beta_6 T + \delta_t + \rho_s + \epsilon_i \quad (3.19)$$

with the same added regressors as above. Gas prices used are in real dollars, so reported estimates of β_1 are in changes in time per dollar. The choice to use a linear specification comes from most participants reporting zero for many of the travel activities, which would cause problems in utilizing a log function for time. A log-linear relationship with log prices could also have been estimated, but the results from a linear estimation provide for an easier interpretation of the coefficients.

To determine the effect of gas price level changes and public transportation availability/utilization on the likelihood of certain modes or purposes of transportation being reported in the diary day by the respondents, a logit model is estimated as follows:

$$ln\left(\frac{(Pr(t_j > 0)}{(1 - Pr(t_j > 0))}\right) = \alpha_0 + \gamma_1 P_{st} + \gamma_2 A_{it} + \gamma_3 P_{st} * A_{it} + \gamma_4 X_i + \gamma_5 U_{st} + \gamma_6 T + \delta_t + \rho_s + \epsilon_i \tag{3.20}$$

Each of these two regressions were performed on the entire sample and on the five different subgroups of income in $25,000 increments for respondents for which income was reported. Robust standard errors are reported, clustered at the state level. As discussed above, time spent traveling was divided into three different purposes: work, leisure and other. Time was also aggregated into three different modes, by car (as a driver or passenger), by public transportation (via rail or bus, excluding ferries), and by self-propelled means (walking, running or biking). Other modes of transportation not listed were not aggregated, but are included in total time spent traveling for various purposes, although these amounts are negligible.

The choice of OLS over a Tobit estimation is deliberate. Time use data frequently include a large number of “zeroes” in the diary period (one day) and do not include all information about the frequency of activities unreported (or reported, for that matter) over a week or even over an “average day”. This is particularly true as weekend and weekday routines are frequently very different for most individuals. A Tobit model would then seem appropriate, incorporating some latent demand to participate in an activity but for which it was not reported. This however belies an awkward way of thinking about the decision of how time is allocated since it would assume the process of deciding to participate in an activity is the same as the choice as its length. An alternative approach would be to estimate the probability of performing an activity and length in a two-step regression to be included in the appropriate causal regression (Cragg, 1971).

Stewart (2009) simulated the performance of these approaches for time use data, finding that the Tobit estimates were much more biased, particularly as the number of instances of an activity declined. OLS estimates were the most unbiased even as compared to the two-step approach but all three performed well as more data were available through longer diary periods. He noted Foster and Kalenkoski (2010) found similar properties of the biased result of the Tobit model when diary time was small. In light of the short diaries in ATUS, I have decided to report the OLS estimates of the above regression which will show the *average* effect of the interested covariates on the time use in question.

3.6.1 Value of the included interaction effect

To determine how useful the included interaction effect is in estimating the combined effect of gas prices and public transportation availability, Table 3.5 provides results from the above regression by first reporting the coefficient of the real price of gas from a regression that does not include the public transportation or interaction variable, then provides results by including just the public transportation usage variable and finally by including all three variables[10]. These results are repeated in the four columns for time spent on all travel, car travel, public transportation and self travel and for the four rows for time spent on all purposes of travel, and three specific purposes of transport: work, leisure and all other travel.

The magnitude of the coefficients for the effect of real gas prices on travel time do

[10]Similar results for income bins used in following analyses are available upon request

not change significantly with the inclusion of the public transportation variable, but both the coefficient on gas prices and public transportation exhibit large changes once the interaction variable is included. For example, in examining travel via any mode for any purpose in the upper-left most square, I find that higher gas prices actually have an effect that is two-thirds greater when accounting for public transportation and its interaction. Further, public transportation usage in the metropolitan area has no direct effect except through its interaction with gas prices. That is, higher levels of public transportation usage for the population result in less of an impact of gas prices on total travel time for survey respondents. Similarly, higher levels of gas prices lead to increases in total travel time if public transportation usage is higher in the respondent's metropolitan area. Interaction effects don't always matter, however, particularly in the case of commuting (second row), regardless of mode of transport, indicating a general trend that the existence of public transportation already induces mode substitution in work-based travel. Further changes in gas prices do not make such an effect stronger.

3.6.2 Mode of Travel

The third column in each cell of Table 3.5 provides a summary of the OLS coefficients resulting from regressing time spent on all travel, car travel, public transportation and self travel on the real price of gas, public transportation usage and their interaction, along with all other control variables described above. These results are then broken down into each of the three different purpose types. All travel is reduced by about 4.5 minutes per average day or around a half-hour a week for a one dollar increase in the real price of gas. Total time traveling in a car is reduced even more than this amount at 4.6 minutes per average day, with small and statistically insignificant increases occurring in time spent in public transportation and self-transport. Increased public transportation availability/utilization does not increase total travel time, but this is due to decreases in car travel time (0.85 min per week) being offset by increases in public transportation and self-transport time (0.31 and 0.39 minutes per week respectively). Over all respondents, increases in public transportation availability dampens the negative effect of gas price increases on overall travel time with interaction effects being weakly positive for all modes. This may reflect respondents living in metropolitan areas with higher levels of public transportation utilization also being closer to the "subsistence" level of driving. This would mute the elasticity of car travel with respect to gas prices as opposed to increasing the effect of higher gas prices.

For all respondents, the effect of an increase in real gasoline prices does not result in large shifts in travel behavior for commuting. A statistically insignificant 0.69 minutes per average day (4.8 min/wk) decline in time is reported for driving along with a 0.31 minutes per average day (2.2 min/wk) increase in public transportation time. Slightly larger, but also statistically insignificant declines in the duration of non-commuting, non-leisure based travel are also found. The amount of time in leisure-based travel, however, falls among all modes, with 2.85 minutes per average day (20 min/week) of a total 3.4 min per average day (23.7 min/week) coming from a decline in car usage. Again, the interaction variable has a dampening effect on the decline indicating larger MSAs, or at least those with more public transportation may have more easily accessible services and business which require less need to reduce travel time or for which gas expenditures are less of a component of overall travel expenditures and household expenditures as a whole. Other travel shows little change across modes of transport, totaling an average of less than 4 minutes decline per week across all respondents.

Tables 3.6 and 3.7 present the results of the OLS and logit regressions for each of the three types of modes of transport. The logit provides insight as to whether changes are being made on the intensive or extensive margin. These tables present odds ratios instead of coefficients for easier interpretation with their relevant t-statistics. The reported estimates for the real gas price, for example, are interpreted as the ratio of the likelihood of travel participation between the average gas price and one where the price is one dollar higher. The provided measure is not precisely estimated, as the estimation is only accurate at the margin, however it still provides some measure of extensive margin changes caused by gas price changes. As an example, a ten cent increase will correspond with one tenth the log difference between the reported odds ratio and one. OLS regressions present results in minutes per average day. The signs of this interaction effect differ significantly over the various income groups, which may reflect the concomittant suburban/urban differences. Without intra-metropolitan area variation, theis may be a source of omitted variable bias when interpreting the coefficients.

Car travel time falls with increased gas prices and increased metropolitan area public transportation usage for all income groups, although higher gas prices don't necessarily reduce car travel participation rates. Odds ratios range from 0.81 to 1.24 for different income groups, none are statistically significant and there is no clear trend based on income. Increased public transportation availability does induce declines in car travel times and induces smaller reductions in car travel overall with respect to gas prices. The opposite is found for income groups of those making less than \$25,000 in income and between \$50,000 and \$75,000. Respondents in these ranges exhibit larger negative effects of gas price on car travel on both the extensive and intensive margins as public transportation increases. Respondents in these income ranges may be more likely to be forced to switch when possible due to income effects. Alternatively, the location of housing and employment for those in this income range makes them more able to take advantage of substitution opportunities, but also have preferences towards driving if gas prices are low. This would result in larger reductions in car travel when gas prices increases, as well as have a larger a negative interaction effect when accounting for public transportation. Both income categories exhibit positive interaction effects on public transportation and self-propelled travel, however estimates for the $50,000 and $75,000 are just outside the range of statistical significance at the 95% level.

Higher gas prices do not necessarily lead to overall higher use of public transport. For those in lower income groups, we see higher likelihood of using public transportation, but a lower usage rate for those making above $50,000. The interaction effect is strongest with those making under $25,000 indicating a strong substitution effect towards that mode of travel, however the likelihood of using public transportation is not increasing. Similar results are found for self-travel. The next section separates out the purpose of travel which allows us to tell a richer story about why these usage patterns may be happening.

3.6.3 Purpose of Travel

Tables 3.9 and 3.8 present the results of the logit and OLS regressions for each of the three different travel purpose types: work, leisure and other. There are small but statistically insignificant increases in the likelihood respondents travel for work-related activities and similar decreases in likelihood of travel for leisure related activities as gas prices increase. Indeed, as I will show later, this may be some indication that people are participating in work related activities more often as gas prices increase. Declines in leisure activity travel as a result of higher gas prices are greatest for those making less than \$25,000 and those making between \$75,000 and \$100,000. Public transportation availability does not seem to have any effect on work, but has a small but significant negative effect on participation in leisure travel. Since overall leisure travel time declines as well, this may be the result of trip chaining or "clustering" of leisure activities when public transportation is more available. This would explain both coefficients and also why there is very little effect of public transportation on leisure travel of those making above \$100,000 who would be theoretically less susceptible to both substitution and income effect related changes. For those making less than \$100,000, the interaction effect on leisure travel time is positive, indicating higher levels of public transportation induce smaller declines in leisure travel based on higher gas prices.

Table 3.10 show changes for work travel, where there is little change across all categories as this is generally considered to be of inelastic demand. There is some indication that car participation rates decline as public transportation availability increases, but not for all income groups. There is little indication that more public transportation make public transportation more likely to be used as gas prices increase. That is, while increases in real gas prices increase the likelihood of using public transportation to work, having more than another city does not indicate such rises would be larger. Self travel is more likely to be used for lower income groups as gas prices increase regardless of public transportation levels, but for those making between \$50,000 and \$100,000, such self-transport is less likely to be true.

Leisure travel participation rates in a car decline for certain income groups as seen in Table 3.11, and for each of these there is evidence of higher participation rates in public transportation as gas prices increase. For the second income group making between \$25,000 and \$50,000, just a 10 cent increase in the gas price is estimated to increase public transportation participation by 11 percent[11].

For other travel in Table 3.12, participation rates for car travel change very little as gas prices increase. Public transportation and self travel is more likely to be utilized by the second income group, as further evidence they practice transport substitution as gas prices increase. However, for income groups above \$50K, increase in real gas prices induce much less participation (although not statistically significant). It is unclear why this would be, but it is clear that the travel for these activities is much more inelastic for those with lower household incomes. This is substantiated by the positive (or alternatively less negative) effects estimated for the low income groups.

3.6.4 Income groups

Of the respondents reporting household income between \$0 and \$25,000, there is an positive direct impact of gas prices on work travel across all modes of transportation, although it is imprecisely estimated. Of note, they are the only income category to exhibit this sign. An increase in work travel time is much more plausible for low income individuals who, due to an increase in difficulty in traveling to work because of higher gas prices putting a strain on their limited resources, may need to take more circuitous and time intensive routes or may need to increase the number of instances of work itself. These increases are small and only total about 6 minutes per week. Similar results are found for other travel which is likely to also be derived from an inelastic demand. However as public transportation usage increases, the interaction coefficients are large and positive for public and self transportation for other travel, indicating substitution towards more time-intensive transportation modes for this type of travel demand. Each additional percent metropolitan area public transportation usage results in an extra 0.6 minutes combined per dollar in-

[11] This is calculated by taking the tenth root of the presented odds ratio of 2.87 which is for a dollar increase.

crease in gas prices. A public transportation usage measure of 6% would yield an extra 25 minutes of such travel per week for a dollar increase in gas prices. Leisure travel is negatively affected by an increase in gas prices, although this is mitigated as public transportation is utilized in the community.

Respondents reporting household income between $25,000 and $50,000 report a pronounced shift from car to public transportation and self-transportation that is even larger in magnitude, a result of this group traveling more in general and also they are more likely to take advantage of a substitution effect. That is, those who are at the lowest incomes are much more likely to take advantage of the lowest cost method, regardless of the price of gas due to their income and relatively lower value of time. Car travel declines by 4.8 minutes per day (34 minutes per week) while travel by public or self transportation increases by 19 minutes per week on average. The popularity of public transportation usage has a positive effect on the impact of gasoline prices indicating the measure may be correlated with car-based leisure travel in some way for this subgroup.

As above, there is little change in work travel for those making between $50,000 and $75,000 if gas prices increase but total declines of about 37 minutes per week between leisure and other travel. Interaction effects are fairly large for overall car travel, with a 6% metropolitan public transportation usage resulting in a 3.2 minutes per day decline in car usage per dollar increase, on top of the baseline measure. This would result in an about a 50 minute decline in car usage per week for a dollar increase in gas.

This measure is of the same magnitude for the next income group at $75,000 and $100,000, but with the complete opposite sign. A 6 percentage point increase in metropolitan public transportation usage would result in a 3.1 minutes per day increase in car usage per dollar increase, but this is from a much higher decline of -10.2 minutes per day baseline estimate. It is unclear what the major locational or preference differences between these two income groups would be; it may come from major differences in levels of suburbanicity or locational decisions relative to public transportation. These effects are mainly manifested within leisure travel which has positive interaction effects in this income group for all mode categories. A omitted variable possibility may be that in metropolitan areas which have both high public transportation usage and high gas prices, leisure travel is also high. This may explain the strange behavior on these interactions. Another possibility is that if we continue the story that these households may be located in areas with lower amounts of public transportation, it may be that the cost of living is lower in those areas or possibly they may be located closer to work, both of which would dampen the negative income effect.

Those with the largest income levels illustrate small effects across the board. They are more likely to use public transportation, which may be a result of being more likely to have homes or jobs in urban centers (relative to those in the immediate lower income bin) as well as a higher preference for such travel. Overall though, they actually look most similar to the lowest income group, indicating that they would also not see very much of a change in transportation habits, although for the opposite reason of having enough income and/or wealth to absorb any increase in gasoline prices.

The model described above predicted that an increase in gas prices would lead to a reduction in activities for which gas consumption is a complement towards other substitutable activities. For our empirical analysis, this meant a reduction in car travel and, due to differing signs for the substitution and income effects, an unclear prediction on travel using public transportation or self-propelled means. For travel derived from an inelastic demand, such as for commuting, it would be much more likely to see only substitution effects. A better availability of public transportation, which is assumed from a higher estimate of utilization of public transportation in the metropolitan area, should make substitution easier but it would also result in households already taking advantage of lower-cost transportation options and be closer to necessary "subsistence" car travel. Therefore, the predicted sign for the interaction of public transportation and gas prices was undetermined.

It is clear from the regression analysis that low income individuals rely on public transportation when living in areas where public transportation systems are more utilized, but those making below $25,000 do not necessarily utilize public transportation much more when gas prices increases. This is likely because they are already exploiting their lowest cost options for transportation and any changes in transport behavior is found towards bike/walk modes. Additionally, it is those in the lower-middle class making between $25,000 and $50,000 that switch towards public transportation the most. Further, this particular subgroup also appears to make such transportation substitutions for leisure travel as well, or at the very least display evidence that their substitution effect surpasses any negative income effects due to increases in gas prices. The welfare benefits of public transportation, *in the context of rising gas prices*, appear to benefit this second income group more than the others, although the lowest income group does appear to rely on public transportation more heavily than all other groups regardless of the gasoline prices. There is also strong indication that the highest income group, those making above $100,000 utilize public transportation for work and leisure travel more as gas price increase, although such changes are small in the context of the larger amount of transportation they participate in. It is also clear that those in the middle-to-upper middle class households do not utilize public transportation as much as a substitute when gas prices increases, either because of a residential or occupational location choice within a metropolitan area away where it is not useful for them or for other preference reasons.

As they are less likely to display evidence of substitution in transportation choices, the $75,000-$100,000 income group thus exhibit the largest evidence of income effects by being the group which displays the largest increases in at-home leisure of television watching. Television watching, it should be noted, generally is an inferior activity (the time spent doing so declines with income). Thus, large increases in television watching, whose proliferation and zero marginal cost make it an ideal baseline replacement leisure source, is a sign of large negative income effects. By that singular metric, it is the upper middle class which bears a strong share of the burden of gas price increases in terms of time use behavioral changes. The lower middle incomes, however, of working much more when gas prices increase, presumably giving up previous time which was spent either doing unpaid work which is passed to someone else or remains undone, or alternatively giving up leisure time.

3.6.5 Sensitivity Checks

To determine if the results of the above regressions are robust to alternative specifications and other measures of public transportation attractiveness, I perform the OLS estimation procedure outlined by Equation 3.19 in three alternate ways. I use the same data but exclude cities with the highest level of public transportation usage, I introduce a measure of metropolitan area density and I use alternate an data source to measure public transportation usage and attractiveness. These results can then be compared to Tables 3.6 and 3.8 to determine if the estimates are sensitive on the choice of sample or data.

One concern about the above results is that they are driven by respondents in cities with high levels of public transportation attractiveness. To determine if this is a concern, the regressions on the major travel time categories were re-estimated without respondents who live in the metropolitan areas with the five highest levels of public transportation utilization based on the ACS estimates[12]. These cities constitute about 16% of the sample and each has a metropolitan public transportation utilization estimate of above 10%. While reduced sample size leads to higher standard errors, this exclusion of a large source of social consistency that might exist across respondents within a metropolitan area is a significant contributor to larger standard errors as well.

Results from these regressions are found in Tables 3.13 and 3.14. Some of the largest differences in coefficient estimates occur at incomes below \$50,000 and above \$100,000. Strong effects which are generated at the full sample between \$25,000 and \$50,000 are seen at the lowest income bracket without the excluded cities. For the lowest income category, this could be a result of differences in nominal incomes as well as a result of a higher economic requirement to have access to car within a given metropolitan area. Relative to suburban and rural areas, parking generally requires either a higher monetary cost for a parking spot or a temporal cost to find available parking in urban areas. It may be the case that the poor in those excluded cities are particularly inelastic with respect to gas prices (due to a lower need to have a car in the first place), resulting in higher responses to car travel and public transportation in remaining cities. Since most of the decline in travel time due to gas prices is generated to to leisure-based car travel, it appears that the declines are related to transportation that can be avoided.

[12] These metropolitan areas are New York, NY, Chicago, IL, Washington, DC, San Francisco/Oakland, CA and Boston, MA.

Those respondents from households in the highest income category also appear to be more elastic with respect to gas prices when the public transportation heavy cities are excluded. Incidentally, most of the difference appears to also be derived from leisure-based car travel, which are displayed as large responses in both specifications for the \$75,000 to \$100,000 income levels. Presumably, this may be due to high and low income households being more likely to be located in city centers in these metropolitan areas relative to others. Each of those five cities are known for high property value neighborhoods in addition to higher levels of access to public transportation. Work-based travel appears to be slightly more responsive to both gas price and public transportation variability in the excluded sample.

It is still the case, however, that the interaction effect is very strong amongst the poor for public transportation utilization and it appears to be driven by non-work related travel. This implies that switching to public transportation or self-propelled means is an important element of low income respondent's response to higher gas prices. Much smaller changes for work-related travel could be the result of already sourcing the lowest cost means of transport for such purposes or that the value of their commuting time is much more important than for travel time associated with other purposes. These overall effects could also be generated by intra- or inter- city migration of poor households who know they could specifically benefit from public transportation to areas where higher levels of public transportation availability and usage exist.

As a second specification check, additional regressions were performed utilizing density of the metropolitan area as an explanatory variable. These results, presented in Tables 3.15 and 3.16 generated only small changes in the coefficient estimates. Density has a substantially positive impact on the transportation time of the poor via walking or biking; an increase in density of only 100 persons per square mile can lead to additional 1.88 minutes per day (13 minutes per week) of self-propelled travel. Thus, the measurement of the effect of gas prices and public transportation is robust to the inclusion of density.

There may also be a concern that the variable being used as a proxy for public transportation attractiveness is unreliable. The ACS estimate of public transportation usage is itself subject to sampling and statistical error and average usage for commuting may not necessarily be an appropriate proxy for overall attractiveness. The ACS measure was used because its geographic identification by CBSA is the same as that used by the CPS, as opposed to the Urbanized Areas of the NTD. While ACS city-level estimates are not considered accurate on a yearly bases, the availability of an average estimate of public transportation usage for 2005-2009 matches would be more accurate. can be connected with the relevant time frame for the sample.

The ACS measure, however, only measures usage for commuting and could be sensitive to the sampling design and the ability of the ACS to generate a representative sample. Usage measured in this limited way may not necessarily be the best proxy for attractiveness which could also be dependent on the attractiveness of the road and highway infrastructure. It would be reasonable to believe regional road and public transportation system attractiveness is correlated with each other, although it is unclear the direction such a relationship would go.

To determine if the results are dependent on this measure, I utilize two alternative measures of public transportation attractiveness, usage and availability from the National Transportation Database (NTD), administered by the Federal Transportation Administration (FTA). Public transportation authorities report a variety of annual metrics for collection. In recent years, the FTA has reported some of these measures by Urbanized Area, collecting data from different transportation modes and systems from the same metropolitan area into one measure. I utilize the earliest agglomeration provided by the FTA from 2008 and apply it to the ATUS sample. While variation in individual years may be preferred, arguably 2008 would be the most appropriate year to use during the sample time frame (2005-2009) as it included the largest variation in gas price and macroeconomic conditions.

Urbanized Area classification was then matched up with the CBSA classification of respondents in the ATUS sample. A very small number[13] of relevant CBSA did not have available data provided in the NTD. The number of passenger-miles and total operating expenses per metropolitan area were divided by population to generate per capita measures for 2008. Both are strongly correlated with the 2005-2009 ACS public transportation usage estimate; passenger-miles per capita has a correlation of 0.8913 and operating expenses per capita has a correlation of 0.8586. Excluding the five cities above with the highest ACS public transportation usage, these correlations are 0.785 and 0.794, respectively.

Results of regressions on time spent traveling by mode and purpose performed using these measures in place of the ACS estimates are found in Tables 3.17 - 3.19. The differences in relative units and measurement techniques, do not allow for easy economic comparison of the results, however, there is significant overlap between these estimates and those found in Tables 3.6 and 3.8 with regards to statistical significance and relative magnitudes between income categories. All three appear to be measuring the same statistical changes, providing evidence the economic measurement of the coefficients is closely related to metropolitan area attractiveness.

One final concern is the assumption that the relative speeds of each of the modes

[13]Sample size falls by 79 or 0.00187%.

of transport could result in biased results. Public transportation service expansion may more likely target commuting behavior and thus its usefulness relative to driving are different for different modes or days of the week. This paper does not empirically seek to show such concerns are necessarily invalid, but fruitful future research might seek to show how intertemporal differences in the relative prices of transportation affect the choice and timing of activities. However, for the purposes of this paper, each regression includes a control for the day of the week, and to the extent the utilized measures of transportation usage and attractiveness differentially effect each purpose, they are estimated separately. The interpretation of the coefficients that proxy for public transportation attractiveness is that they represent the average effect of how public transportation is implemented across all respondents, including inter- and intra-city differences.

3.7 Policy Implications

3.7.1 Public transportation as an enhancement to the advantages of agglomeration

One important reason to measure the differential effects of gas prices and public transportation lies in the the importance of public transportation for low income individuals. As Glaeser et al. (2008) noted, a key influence of poor individuals' attraction to cities is for their better public transportation. Given the poor appear to have much larger impacts of travel reduction with respect to gas prices when the largest cities were excluded, there would appear significant advantages for the poor in expanding public transportation in other cities. While the theoretical impact of public transportation on improved employment prospects has been touted, they have been limited in their empirical findings. Fan et al. (2012) and Blumenberg and Manville (2004) argue that this could be the result of the difficulty in measuring transit effectiveness and controlling for intervening factors as well as simply a failure of actual transit policy to be responsive to this need. Fan et al. (2012) find strong evidence of increased job accessibility in the expansion of light rail in the Minneapolis metropolitan area. According to the estimates generated in this paper, increased public transportation usage and spending generate more work-based travel. This may be because public transportation is less time efficient than driving (but more convenient or cheaper to attract its use), but at the same time, the results suggest that higher public transportation attractiveness could encourage more labor market activity.

In light of this, decisions of new service could improve employer and employee matching by ensuring such connections are made, even if such service does not necessarily connect the central business district with outlying residential neighborhoods. While this appears to be an obvious statement, most subway and train systems, which are generally much faster than via bus, do not have lines which do not traverse through the central business district. Even New York City's extensive subway system does not include any subway lines which connect the outer boroughs while avoiding Manhattan. In lieu of new lines, liberal density zoning around public transportation stations and hubs, particularly for industries that employ low wage workers, could improve the effectiveness and attractiveness of existing systems.

Such benefits also exist with respect to leisure based activity. The largest declines in transportation due to higher gas prices come from leisure-based car travel. This appears to be true for respondents in both middle income and lower income households. Higher levels of public transportation appear to reduce the negative impact of gasoline prices on travel for leisure more than any other purpose. This could be in part due to the denser nature of metropolitan areas with higher levels of public transportation and thus, income effects of higher gas prices would be lower, but this persists even when income is controlled for.

Higher levels of public transportation usage reduces overall leisure travel time and reduces the impact of gas prices on leisure travel. This is consistent with it facilitating leisure travel more efficiently and making it more inelastic with respect to gas prices. This provides evidence that public transportation facilitates leisure-based economic activity to the extent local economies depend on leisure time (and presumably money) being spent in the local economy as opposed to activities at home. Again, allowing for density of commercial activity around public transportation facilitates improved economic activity and heightens any advantages public transportation provides. This paper provides arguments for proponents of both density and expansion of public transportation that both would be economically beneficial and it would appear, purely from the perspective of household time use decisions, it would provide benefits in a progressive manner. The estimated interaction effects suggest the economic benefits would only increase if real energy prices rose in the future.

3.7.2 Impact on environmental policy

One of the goals of gasoline taxes, in addition to collecting revenue to offset the external damage of carbon emissions, is to reduce carbon emissions themselves. One argument used against increases in such taxes at the federal or state level is that such taxes are regressive. As noted earlier, research indicates this is true when regressivity is measured based on the proportion of income devoted to gasoline for drivers as opposed to the overall welfare impact. The estimates of the impact of gas prices from this paper support such an argument as well. As noted in the description of the model, the welfare losses associated with an increase in the price of gas can be shown to be proportional to the number of vehicle miles traveled by the individual. While those data are not available in my sample, there are data on the amount of time spent driving. By utilizing a series of assumptions to make conversions, I can construct a crude measure of welfare loss.

Table 3.21 presents the incidence measure for a 10% increase in the price of gas from a starting price of \$2.50. Measurements are made for each of the income bins as well as for different levels of the ACS measure of public transportation in the respondent's metropolitan area. The first row represents the welfare loss per year due to the price change and the second row represents this welfare loss as a percentage of income. These were calculated by first estimating the average number of minutes per day of car-based travel per income group for a price of \$2.50 and for different levels of metropolitan public transportation usage. The lost consumer surplus of the \$0.25 increase was generated by dividing the miles per day by 60 (to get hours per day), multiplying by an average speed of 25 miles per hour and dividing by an average miles per gallon of 23. This generates welfare lost per day and this was multiplied by 365 to get yearly loss. Since individual income levels are not known, the consumer surplus to income ratio was generated using the midpoint of each grouping, with \$150,000 being used for the upper bin.

The results of this paper then also show that public transportation availability may help alleviate such concerns about regressivity and may make higher gasoline and carbon taxes more politically feasible. West (2004) examines the alternate impact of vehicle-based tax or subsidy plans geared towards reducing emissions and finds that most would be even more regressive than gasoline taxes. Parry and Small (2009) note that distributional concerns are likely more efficiently addressed through the general tax and benefit system, but provide strong evidence that existing public transit subsidies are warranted on overall efficiency grounds. Seen in this light, public transportation subsidies can also reduce the regressiveness of gasoline taxes.

Bento et al. (2009) as well note that if gasoline tax revenue is directed back towards lower income individuals, the plan can be progressive. The concern, however, is that such a plan might not actually reduce carbon emissions. It is unclear, both from this paper and others, that gasoline prices will actually reduce emissions to a significant amount. While Davis and Killian (2011) do note longer horizons might lead to increased effects of gasoline taxes, they estimate the short run effect of a 10-cent increase in gasoline taxes would result in emissions falling by roughly one half of the normal US year-to-year increase. Applying their methods to the data in this paper would likely generate results even smaller depending on the relationship between travel time and gasoline consumption[14]

Public transportation provision could then be a more attractive and useful means in reducing automobile usage relative to taxes and subsidies as it can induce migration patterns that reduce driving needs as well as substitution for existing residents. Utilizing gas tax revenue to subsidize public transportation as is more common in European countries, as opposed to subsidizing highway construction, may enhance the reduction of carbon emissions. The results of this paper suggest, however, that remaining drivers will be more inelastic for preference based reasons (as opposed to economic), so there may be limits to reducing driving, and thus carbon emissions, in this fashion. Additionally, research devoted to the impact of public transportation on congestion and driving has found little evidence for that to be the case (Downs, 1962; Cervero et al., 2002; Duranton and Turner, 2011; Lee and Senior, 2013). Such studies are usually performed at the metropolitan level, however, and do not reflect the impact investment in public transportation might have on larger regional or national level.

[14]Their finding is extrapolated from their estimate of a 10 cent gas tax reducing gasoline consumption by 1.3%. My estimates suggest a 10 cent gas tax reduces time spent in car travel by .46 minutes per day. This is 0.6% of the mean car travel time.

Finally, this paper does not account for changes in the composition of driving, particularly with respect to increases in the incidences of commuting with another individual. DeLoach and Tiemann (2012) presents evidence from the ATUS of higher gas prices leading to an increase in carpooling during the same time frame as this study, but admit the results are fairly modest.

3.7.3 Health policy

Gas taxes may impact health through the substitution of transportation to modes with positive health externalities. Courtemanche (2009) found a link between increased gas prices and a decrease in obesity. The results of the paper are mixed in that respect. An increase in gas prices does induce an increase for most income groups in biking and walking as a transportation activity, although notably there is a negative effect (of marginal statistical significance) effect for those making between $50,000 and $75,000 and $75,000-$100,000. This negative result persists when density is controlled for as well. This is likely due to a negative income effect generating less demand for travel overall[15]. Additionally, it should be noted that if minimal changes in such behavior occur for at-risk groups, such as the households with lowest income, they may be making other substitutions which will not show up in time use data that could negatively affect their health. For example, poorer eating habits may occur by shifting towards grocery purchases of sale items and lower cost foods which tend to be lower in quality (Gicheva et al., 2007).

Low income individuals are more likely to rely on public transportation and thus feel less of a burden of increases of gas prices, but when such availability does not exist, they are also likely to have inelastic demand and a lack of wealth to absorb

[15]As a reminder, this categorization only includes walking or biking for transportation purposes. Unincluded results of similar regressions of gas prices on time spent in sports and exercise activity yield no clear trend in either direction.

income effect shocks. The relative inelasticity of low income travel behavior found is consistent with this interpretation. As such, they would then face an incredible burden of finding a way to pay for transportation as well as their other needs relative to those with higher incomes. Thus, a wider variety of transportation options would have positive impacts on the ability of low income individuals to achieve healthier outcomes.

The time use data is a valuable resource to complete a picture of responsiveness to market changes that previously has been examined only with consumption data. Based on the results from this paper, income groups may vary greatly in their response to gas prices, and their activity decisions matter greatly in how those responses are manifested. Public transportation allows individuals to utilize a lower cost option than driving, but the changes are not always economically or statistically significant and the income effect caused by continued usage of gasoline or related goods and services can lead to negative impacts on all means of transportation as people stay home for activities. This can impact economic activity both in terms of choices of leisure as well as options for employment. This paper provides does not provide evidence that public transportation significantly reduces overall driving nor does it increase the effectiveness of gasoline taxes in doing the same. That said, there is value in public transportation in reducing welfare losses associated higher gas prices. In addition, there is the potential for increased economic activity when land use policies enable housing and commercial development in areas where public transportation is already servicing.

3.8 Figures and Tables

Table 3.1: **Summary Demographics by Income**

Variable	$0-$25K	$25-$50K	$50-$75K	$75K-$100K	$100K+	ALL
Age	47.0	44.5	42.7	42.0	42.4	43.9
Female	0.64	0.57	0.55	0.52	0.50	0.56
Any HH Children	0.60	0.55	0.45	0.38	0.33	0.47
Child Under 6	0.20	0.20	0.24	0.26	0.25	0.23
HH Partner	0.26	0.44	0.61	0.71	0.77	0.54
Employment Status						
Employed	0.494	0.686	0.763	0.791	0.802	0.700
Retired	0.211	0.146	0.080	0.056	0.040	0.112
Not in Labor Force	0.431	0.267	0.197	0.171	0.172	0.254
Educational Attainment						
no HS degree	0.392	0.280	0.135	0.077	0.117	0.151
High School	0.296	0.341	0.187	0.095	0.081	0.227
Some College	0.192	0.306	0.223	0.137	0.143	0.270
Bachelor's	0.072	0.205	0.220	0.185	0.318	0.225
Prof. Degree	0.048	0.133	0.177	0.186	0.457	0.127
2005-2009 ACS estimate of public trans. utilization	4.67	4.81	4.96	5.71	7.05	5.39
Observations	7,441	9,842	7,230	5,028	7,587	37,128
Sample Proportion	0.200	0.265	0.195	0.135	0.204	

Proportions reported in all cases except for age.

Table 3.2: **Weighted Mean Travel Times in Minutes per Average Day**

Variable	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+	ALL
Total Travel	76.11	82.56	88.12	89.74	95.36	85.94
	(75.08)	(74.69)	(79.35)	(80.90)	(85.49)	(79.10)
Car Travel	58.11	71.81	78.76	79.85	83.06	73.81
	(62.34)	(66.38)	(70.86)	(71.84)	(69.08)	(68.38)
PubTran Travel	5.643	2.950	2.274	2.352	2.458	3.177
	(31.94)	(19.33)	(16.78)	(17.50)	(18.03)	(21.62)
Self Travel	10.72	4.859	3.454	3.518	3.466	5.294
	(36.51)	(21.15)	(17.48)	(18.46)	(16.23)	(23.51)
Work Travel	11.88	15.11	17.02	19.52	19.04	16.23
	(31.79)	(31.32)	(34.24)	(38.61)	(39.96)	(35.02)
Leisure Travel	28.18	29.35	31.35	30.88	33.06	30.47
	(51.99)	(49.00)	(54.41)	(57.67)	(56.54)	(53.49)
Other Travel	36.05	38.10	39.76	39.34	43.25	39.23
	(51.72)	(55.52)	(56.42)	(55.80)	(62.35)	(56.52)

Standard deviations in parentheses.

Table 3.3: **Weighted Mean Activity Times in Minutes per Average Day**

Variable	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+	ALL
Sleeping	538.0	517.5	505.6	501.2	497.7	513.0
	(147.6)	(134.2)	(125.0)	(118.2)	(112.5)	(129.9)
Working	131.5	185.0	202.7	208.7	206.4	185.3
	(217.3)	(246.6)	(254.0)	(252.6)	(255.9)	(246.9)
Eating/Drinking	62.14	66.38	69.87	70.52	77.23	68.99
	(49.52)	(49.95)	(50.39)	(49.76)	(52.76)	(50.76)
Socializing/Leisure	313.6	277.2	249.8	233.3	222.3	262.0
	(208.5)	(189.7)	(176.3)	(164.4)	(161.6)	(185.3)
Sports/Exercise	14.14	17.71	21.49	24.91	29.80	21.17
	(50.77)	(57.74)	(63.61)	(68.03)	(71.06)	(62.26)
LEISURE ACTIVITIES						
Television and movies	181.5	156.2	135.4	121.6	110.4	143.1
	(171.9)	(149.3)	(136.0)	(120.2)	(113.6)	(143.7)
Playing games	10.97	10.41	9.803	8.116	8.202	9.640
	(49.22)	(46.86)	(45.43)	(37.61)	(39.47)	(44.50)
Reading	21.80	21.10	19.23	20.37	23.78	21.32
	(59.49)	(55.76)	(49.00)	(48.57)	(51.97)	(53.61)
Computer use (exc. Games)	6.249	8.176	8.402	9.884	9.261	8.287
	(34.86)	(36.41)	(34.16)	(36.90)	(34.54)	(35.38)
Socializing	6.724	7.628	8.585	7.778	9.319	7.999
	(43.54)	(45.02)	(47.40)	(43.01)	(48.46)	(45.67)

Standard deviations in parentheses.

Table 3.4: **Estimated Elasticity of Car Travel Time**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
Real Price Gas (\$)	-0.0976***	-0.0212	-0.102*	-0.177*	-0.152	0.0181
	(0.0274)	(0.0717)	(0.0428)	(0.0667)	(0.0880)	(0.0524)
Real Price Gas (\$)	-0.132***	-0.0142	-0.148**	-0.119	-0.269**	-0.0430
	(0.0219)	(0.0850)	(0.0435)	(0.0756)	(0.0927)	(0.0576)
Public Trans Usage (%)	-0.0372***	0.00973	-0.0529	0.0691	-0.120***	-0.0491
	(0.00945)	(0.0408)	(0.0371)	(0.0381)	(0.0282)	(0.0261)
Interaction	0.00746***	-0.00141	0.0112	-0.0129	0.0222***	0.00899
	(0.00181)	(0.00758)	(0.00679)	(0.00696)	(0.00543)	(0.00489)
Observations	40000	6344	9265	6976	4860	7371

Standard errors in parentheses

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

Table 3.5: **Effect of Gas Prices and Public Transportation on Transportation Times (all incomes)**

	ALL			Car			PubTran			Self		
ALL TRAVEL												
Real Price Gas ($)	-2.922*	-2.683*	-4.490***	-3.240**	-3.359**	-4.609***	0.307	0.479	0.0790	0.0843	0.244	0.108
	(1.302)	(1.285)	(1.001)	(1.035)	(1.030)	(0.854)	(0.377)	(0.378)	(0.288)	(0.315)	(0.315)	(0.366)
Public Trans Usage (%)		0.665***	-0.0811		-0.332*	-0.849***		0.479***	0.314***		0.445***	0.389
		(0.124)	(0.143)		(0.143)	(0.228)		(0.133)	(0.0850)		(0.114)	(0.211)
Interaction			0.334***			0.231***			0.0739			0.0252
			(0.0914)			(0.0599)			(0.0432)			(0.0472)
WORK TRAVEL												
Real Price Gas ($)	-0.521	-0.415	-0.376	-0.723*	-0.723*	-0.692	0.172	0.245	0.315*	0.0448	0.0646	0.0148
	(0.549)	(0.530)	(0.484)	(0.350)	(0.349)	(0.371)	(0.155)	(0.159)	(0.148)	(0.0547)	(0.0539)	(0.0576)
Public Trans Usage (%)		0.296***	0.313***		-0.000907	0.0121		0.203***	0.232***		0.0552***	0.0346
		(0.0610)	(0.0858)		(0.0456)	(0.109)		(0.0463)	(0.0404)		(0.0119)	(0.0274)
Interaction			-0.00722			-0.00581			-0.0130			0.00921
			(0.0517)			(0.0356)			(0.0133)			(0.00765)
LEISURE TRAVEL												
Real Price Gas ($)	-2.173**	-2.114**	-3.397***	-1.853**	-1.886**	-2.849***	0.0456	0.0895	-0.0270	-0.213	-0.183	-0.127
	(0.715)	(0.712)	(0.765)	(0.659)	(0.661)	(0.686)	(0.227)	(0.229)	(0.254)	(0.109)	(0.111)	(0.102)
Public Trans Usage (%)		0.165***	-0.365*		-0.0900	-0.488***		0.122**	0.0742		0.0842***	0.107***
		(0.0451)	(0.156)		(0.0481)	(0.0996)		(0.0366)	(0.0402)		(0.0164)	(0.0294)
Interaction			0.237***			0.178**			0.0216			-0.0104
			(0.0635)			(0.0509)			(0.0124)			(0.00791)
OTHER TRAVEL												
Real Price Gas ($)	-0.227	-0.154	-0.717	-0.663	-0.750	-1.067	0.0893	0.145	-0.209	0.253	0.362	0.220
	(0.774)	(0.783)	(0.749)	(0.653)	(0.638)	(0.737)	(0.172)	(0.170)	(0.145)	(0.266)	(0.266)	(0.345)
Public Trans Usage (%)		0.204***	-0.0283		-0.242***	-0.373*		0.154**	0.00819		0.306***	0.247
		(0.0481)	(0.118)		(0.0679)	(0.180)		(0.0518)	(0.0255)		(0.0870)	(0.159)
Interaction			0.104			0.0588			0.0654*			0.0264
			(0.0645)			(0.0592)			(0.0267)			(0.0362)
Observations	42795											

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6: **Effect of Gas Prices and Public Transportation on Travel Time† by Mode**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
CAR TRAVEL						
Real Price Gas (\$)	-4.609***	-2.400	-4.852**	-4.142	-10.18**	-0.933
	(0.854)	(2.750)	(1.796)	(2.947)	(2.919)	(2.181)
Public Trans Usage (%)	-0.849***	-0.584	-1.788*	0.548	-1.292***	-0.849*
	(0.228)	(0.451)	(0.765)	(0.432)	(0.350)	(0.385)
Interaction	0.231***	-0.136	0.634*	-0.536**	0.514**	0.303*
	(0.0599)	(0.187)	(0.289)	(0.189)	(0.149)	(0.143)
PUBLIC TRANSPORTATION TRAVEL						
Real Price Gas (\$)	0.0790	0.383	1.515	-0.808	-1.183	0.403
	(0.288)	(1.079)	(0.826)	(0.527)	(0.595)	(0.688)
Public Trans Usage (%)	0.314***	-0.125	1.190	0.120	-0.150	0.642***
	(0.0850)	(0.260)	(0.603)	(0.128)	(0.233)	(0.0989)
Interaction	0.0739	0.432***	-0.239	0.140	0.179	-0.106
	(0.0432)	(0.119)	(0.169)	(0.0833)	(0.100)	(0.0717)
SELF TRAVEL						
Real Price Gas (\$)	0.108	0.753	1.193	-1.209	-1.104*	0.684
	(0.366)	(1.309)	(0.966)	(0.655)	(0.480)	(0.695)
Public Trans Usage (%)	0.389	0.172	1.302*	-0.0550	-0.131	0.770**
	(0.211)	(0.365)	(0.624)	(0.176)	(0.233)	(0.257)
Interaction	0.0252	0.340*	-0.313	0.171	0.167	-0.210*
	(0.0472)	(0.147)	(0.203)	(0.0995)	(0.0876)	(0.0913)
Observations	42795	7441	9842	7230	5028	7587

Standard errors in parentheses

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

† Travel time is measured in minutes per average day.

Table 3.7: **Effect of Gas Prices and Public Transportation on Travel Participation Rates by Mode**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
CAR TRAVEL						
Real Price Gas (\$)	0.990	1.020	0.814	1.228	0.938	1.236
	(-0.22)	(0.20)	(-1.19)	(0.95)	(-0.19)	(0.82)
Public Trans Usage (%)	0.930***	0.940***	0.860***	0.976	0.985	0.913*
	(-4.26)	(-3.54)	(-4.31)	(-0.64)	(-0.39)	(-2.14)
Interaction	1.001	0.992	1.023	0.969**	0.987	1.004
	(0.14)	(-1.45)	(1.63)	(-3.25)	(-1.06)	(0.34)
PUB.TRANS. TRAVEL						
Real Price Gas (\$)	1.044	1.174	1.474*	0.842	0.583	0.906
	(0.42)	(0.91)	(2.16)	(-0.78)	(-1.84)	(-0.31)
Public Trans Usage (%)	1.096***	1.075**	1.195***	1.081**	1.011	1.170***
	(6.71)	(2.81)	(5.03)	(2.73)	(0.18)	(3.73)
Interaction	0.999	1.009	0.976*	1.016	1.024	0.985
	(-0.33)	(1.35)	(-2.54)	(1.69)	(0.82)	(-1.11)
SELF TRAVEL						
Real Price Gas (\$)	1.049	1.018	1.266*	0.945	0.940	1.033
	(0.83)	(0.18)	(2.47)	(-0.46)	(-0.44)	(0.19)
Public Trans Usage (%)	1.052**	1.037	1.142***	0.978	1.019	1.080*
	(2.72)	(1.36)	(5.64)	(-1.38)	(0.59)	(2.21)
Interaction	0.999	1.012	0.969***	1.030**	1.004	0.990
	(-0.21)	(1.30)	(-4.55)	(3.28)	(0.37)	(-0.67)
Observations	42690	7414	9589	6844	4578	6892

Exponentiated coefficients; t statistics in parentheses

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

Table 3.8:
Effect of Gas Prices and Public Transportation on Travel Time† by Purpose

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
ALL TRAVEL						
Real Price Gas (\$)	-4.490***	-2.504	-3.827	-6.110*	-9.377*	0.161
	(1.000)	(2.931)	(2.037)	(2.763)	(3.681)	(3.271)
Public Trans Usage (%)	-0.0811	0.0767	0.144	0.391	-1.103	0.390
	(0.143)	(0.694)	(0.489)	(0.451)	(0.715)	(0.453)
Interaction	0.334***	0.323	0.341	-0.0822	0.716*	0.127
	(0.0913)	(0.333)	(0.198)	(0.180)	(0.292)	(0.249)
WORK TRAVEL						
Real Price Gas (\$)	-0.376	0.848	-0.488	0.0257	-0.861	-0.427
	(0.484)	(0.838)	(1.027)	(1.355)	(1.733)	(1.408)
Public Trans Usage (%)	0.313***	0.636**	0.388*	0.662***	-0.111	0.178
	(0.0858)	(0.202)	(0.164)	(0.174)	(0.231)	(0.319)
Interaction	-0.00722	-0.163*	0.00972	-0.145	0.0948	0.0530
	(0.0517)	(0.0793)	(0.0672)	(0.0997)	(0.111)	(0.178)
LEISURE TRAVEL						
Real Price Gas (\$)	-3.397***	-3.979*	-1.939	-3.339*	-7.622**	-0.124
	(0.765)	(1.736)	(1.635)	(1.605)	(2.476)	(2.162)
Public Trans Usage (%)	-0.365*	-0.330	-0.0927	-0.374	-1.157***	0.259
	(0.156)	(0.519)	(0.757)	(0.274)	(0.249)	(0.407)
Interaction	0.237***	0.229	0.154	0.119	0.758***	-0.0743
	(0.0635)	(0.233)	(0.346)	(0.148)	(0.141)	(0.215)
OTHER TRAVEL						
Real Price Gas (\$)	-0.717	0.626	-1.400	-2.796	-0.894	0.712
	(0.749)	(2.193)	(1.774)	(2.110)	(1.874)	(2.277)
Public Trans Usage (%)	-0.0283	-0.229	-0.151	0.103	0.165	-0.0465
	(0.118)	(0.583)	(0.450)	(0.404)	(0.485)	(0.414)
Interaction	0.104	0.257	0.177	-0.0561	-0.137	0.148
	(0.0645)	(0.246)	(0.218)	(0.185)	(0.194)	(0.175)
Observations	42795	7441	9842	7230	5028	7587

Standard errors in parentheses

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

† Travel time is measured in minutes per average day.

Table 3.9: **Effect of Gas Prices and Public Transportation on Travel Participation Rates by Purpose**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
WORK TRAVEL						
Real Price Gas (\$)	1.064	1.039	1.028	1.229	1.111	1.040
	(1.36)	(0.33)	(0.34)	(1.45)	(0.69)	(0.36)
Public Trans Usage (%)	1.003	1.028	0.995	1.029	0.967	0.991
	(0.34)	(1.45)	(-0.28)	(0.84)	(-0.65)	(-0.59)
Interaction	0.997	0.988	1.004	0.989	1.006	1.000
	(-0.91)	(-1.37)	(0.52)	(-0.58)	(0.30)	(-0.00)
LEISURE TRAVEL						
Real Price Gas (\$)	0.934*	0.886	0.937	0.981	0.809*	1.000
	(-2.24)	(-1.42)	(-0.92)	(-0.22)	(-2.40)	(0.00)
Public Trans Usage (%)	0.985*	0.986	0.992	0.976*	0.948*	1.018
	(-2.56)	(-0.74)	(-0.40)	(-1.99)	(-2.12)	(0.70)
Interaction	1.005	1.005	0.999	1.006	1.026*	0.993
	(1.70)	(0.57)	(-0.06)	(0.86)	(2.27)	(-0.66)
OTHER TRAVEL						
Real Price Gas (\$)	1.025	1.053	0.994	0.933	1.139	1.044
	(0.64)	(0.67)	(-0.08)	(-0.58)	(1.09)	(0.42)
Public Trans Usage (%)	0.998	0.974*	0.996	0.993	1.041**	0.991
	(-0.37)	(-2.54)	(-0.23)	(-0.41)	(2.96)	(-0.59)
Interaction	1.000	1.012*	1.000	1.001	0.980***	1.007
	(0.07)	(2.45)	(-0.04)	(0.09)	(-3.31)	(0.90)
Observations	42795	7438	9842	7229	5024	7582

Exponentiated coefficients; t statistics in parentheses

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

Table 3.10: **Effect of Gas Prices and PT on Work Travel by Mode**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
CAR TRAVEL - Participation						
Real Price Gas (\$)	1.060	1.077	0.988	1.260	1.141	1.015
	(1.32)	(0.77)	(-0.15)	(1.66)	(0.94)	(0.14)
Public Trans Usage (%)	0.990	1.017	0.946^{*}	1.051	0.963	0.976
	(-1.36)	(0.69)	(-2.17)	(1.83)	(-0.91)	(-1.63)
Interaction	0.992^{*}	0.971^{*}	1.010	0.967^{**}	1.000	1.001
	(-2.56)	(-2.52)	(0.96)	(-2.85)	(0.00)	(0.16)
CAR TRAVEL - Conditional Duration						
Real Price Gas (\$)	-0.692	0.122	-0.953	0.163	-0.951	-1.019
	(0.371)	(0.707)	(0.861)	(1.323)	(1.659)	(0.756)
Public Trans Usage (%)	0.0121	0.156	-0.236	0.511^{*}	-0.0458	-0.345
	(0.109)	(0.206)	(0.241)	(0.208)	(0.235)	(0.212)
Interaction	-0.00581	-0.0917	0.0884	-0.214^{*}	-0.0112	0.153
	(0.0356)	(0.0829)	(0.0794)	(0.0856)	(0.121)	(0.0936)
PUB.TRANS. TRAVEL - Participation						
Real Price Gas (\$)	1.155	1.271	1.188	1.168	0.598	1.355
	(0.98)	(0.85)	(0.52)	(0.34)	(-0.94)	(0.70)
Public Trans Usage (%)	1.136^{***}	1.120^{*}	1.200^{***}	1.128^{*}	1.073	1.266^{**}
	(5.90)	(2.53)	(4.40)	(2.17)	(1.08)	(3.18)
Interaction	0.995	0.994	0.983	1.020	1.017	0.974
	(-1.01)	(-0.46)	(-1.34)	(1.13)	(0.56)	(-1.28)
PUBLIC TRANSPORTATION TRAVEL - Conditional Duration						
Real Price Gas (\$)	0.315^{*}	0.415	0.619	0.100	-0.566^{*}	0.686
	(0.148)	(0.456)	(0.433)	(0.409)	(0.269)	(0.528)
Public Trans Usage (%)	0.232^{***}	0.218	0.568^{*}	0.194	-0.145	0.314^{**}
	(0.0404)	(0.127)	(0.256)	(0.115)	(0.0815)	(0.0978)
Interaction	-0.0130	0.0141	-0.113	-0.00192	0.118^{**}	-0.0562
	(0.0133)	(0.0390)	(0.0698)	(0.0318)	(0.0365)	(0.0624)
SELF TRAVEL - Participation						
Real Price Gas (\$)	1.037	1.087	1.595^{*}	0.867	0.543	1.137
	(0.35)	(0.32)	(2.20)	(-0.66)	(-1.74)	(0.36)
Public Trans Usage (%)	1.053^{***}	1.089^{**}	1.169^{***}	0.907^{*}	0.972	1.165^{**}
	(5.22)	(2.64)	(4.72)	(-2.40)	(-1.15)	(2.91)
Interaction	1.003	0.987	0.973	1.068^{***}	1.033^{**}	0.975
	(0.72)	(-1.24)	(-1.81)	(3.39)	(2.86)	(-1.29)
SELF TRAVEL - Conditional Duration						
Real Price Gas (\$)	0.0148	0.0836	0.264	-0.153	-0.138	0.0220
	(0.0576)	(0.267)	(0.235)	(0.107)	(0.225)	(0.151)
Public Trans Usage (%)	0.0346	0.137^{**}	0.196	-0.0942	0.00940	0.0396
	(0.0274)	(0.0418)	(0.127)	(0.0769)	(0.0482)	(0.0537)
Interaction	0.00921	-0.0366^{*}	-0.0445	0.0679	0.0177	0.00250
	(0.00765)	(0.0167)	(0.0500)	(0.0435)	(0.0184)	(0.0270)
Observations	42795	7441	9842	7230	5028	7587

Exponentiated coefficients; t statistics in parentheses

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

Table 3.11: **Effect of Gas Prices and PT Leisure Travel by Mode**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
CAR TRAVEL - Participation						
Real Price Gas (\$)	0.953	0.934	0.876*	1.049	0.844*	1.028
	(-1.81)	(-0.80)	(-1.99)	(0.65)	(-2.15)	(0.33)
Public Trans Usage (%)	0.973***	0.978	0.947*	0.992	0.960	0.996
	(-3.54)	(-0.92)	(-2.47)	(-0.65)	(-1.80)	(-0.33)
Interaction	1.003	0.992	1.011	0.992	1.015	0.998
	(1.51)	(-0.63)	(1.30)	(-1.52)	(1.63)	(-0.34)
CAR TRAVEL - Conditional Duration						
Real Price Gas (\$)	-2.849***	-2.785	-3.046*	-2.129	-6.576**	-0.646
	(0.686)	(1.672)	(1.249)	(1.399)	(2.365)	(1.604)
Public Trans Usage (%)	-0.488***	-0.280	-0.902	0.0297	-1.048***	-0.170
	(0.0996)	(0.332)	(0.480)	(0.266)	(0.257)	(0.249)
Interaction	0.178**	-0.0231	0.364	-0.166	0.634***	0.0359
	(0.0509)	(0.147)	(0.234)	(0.111)	(0.139)	(0.126)
PUB.TRANS. TRAVEL - Participation						
Real Price Gas (\$)	1.161	1.156	2.868*	0.721	1.174	1.393
	(0.94)	(0.44)	(2.54)	(-0.65)	(0.30)	(0.66)
Public Trans Usage (%)	1.115***	1.065*	1.337***	1.052	1.047	1.460***
	(6.85)	(2.16)	(3.80)	(1.38)	(0.57)	(11.84)
Interaction	0.990	1.000	0.948*	1.022	1.015	0.898***
	(-1.59)	(0.02)	(-2.32)	(1.42)	(0.40)	(-5.39)
PUBLIC TRANSPORTATION TRAVEL - Conditional Duration						
Real Price Gas (\$)	-0.0270	-0.0183	0.876	-0.386	-0.0660	0.325
	(0.254)	(1.075)	(0.511)	(0.446)	(0.223)	(0.283)
Public Trans Usage (%)	0.0742	-0.0714	0.373	-0.0611	-0.0497	0.310*
	(0.0402)	(0.194)	(0.200)	(0.0970)	(0.0540)	(0.129)
Interaction	0.0216	0.152	-0.0965	0.0741	0.0659***	-0.102*
	(0.0124)	(0.0916)	(0.0722)	(0.0576)	(0.0174)	(0.0488)
SELF TRAVEL - Participation						
Real Price Gas (\$)	0.958	0.937	0.928	0.929	0.806	1.070
	(-0.60)	(-0.61)	(-0.50)	(-0.38)	(-1.05)	(0.33)
Public Trans Usage (%)	1.041*	1.020	1.075**	0.982	0.999	1.108**
	(2.29)	(1.18)	(2.84)	(-1.23)	(-0.04)	(3.07)
Interaction	1.000	1.011	0.988	1.026**	1.013	0.982
	(0.07)	(1.38)	(-1.42)	(3.10)	(1.00)	(-1.12)
Observations	42786	7410	9785	7142	4872	7480
SELF TRAVEL - Conditional Duration						
Real Price Gas (\$)	-0.127	-0.0874	-0.126	-0.152	-0.462	0.0117
	(0.102)	(0.279)	(0.221)	(0.294)	(0.362)	(0.205)
Public Trans Usage (%)	0.107***	0.0432	0.316***	-0.0225	-0.0281	0.208**
	(0.0294)	(0.0545)	(0.0362)	(0.0594)	(0.0492)	(0.0664)
Interaction	-0.0104	0.0439	-0.0936***	0.0402	0.0314*	-0.0627*
	(0.00791)	(0.0277)	(0.0138)	(0.0217)	(0.0142)	(0.0266)
Observations	42795	7441	9842	7230	5028	7587

Exponentiated coefficients; t statistics in parentheses

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

Table 3.12: **Effect of Gas Prices and PT on Other Travel by Mode**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
CAR TRAVEL - Participation						
Real Price Gas (\$)	1.013	1.072	0.951	1.001	1.078	1.041
	(0.42)	(0.96)	(-0.74)	(0.01)	(0.54)	(0.42)
Public Trans Usage (%)	0.973*	0.958**	0.961	0.989	1.001	0.977
	(-2.29)	(-3.19)	(-1.11)	(-0.75)	(0.10)	(-1.45)
Interaction	1.000	0.996	1.000	0.992	0.990	1.007
	(-0.04)	(-0.68)	(0.04)	(-0.88)	(-1.51)	(1.32)
CAR TRAVEL - Conditional Duration						
Real Price Gas (\$)	-1.067	0.264	-0.853	-2.176	-2.656	0.731
	(0.737)	(1.834)	(1.623)	(2.189)	(1.637)	(1.682)
Public Trans Usage (%)	-0.373*	-0.460	-0.650	0.00638	-0.199	-0.334
	(0.180)	(0.349)	(0.616)	(0.307)	(0.338)	(0.326)
Interaction	0.0588	-0.0212	0.182	-0.157	-0.109	0.114
	(0.0592)	(0.117)	(0.243)	(0.155)	(0.115)	(0.129)
PUB.TRANS. TRAVEL - Participation						
Real Price Gas (\$)	0.910	0.955	1.143	0.665	0.680	0.844
	(-0.70)	(-0.19)	(0.48)	(-1.03)	(-0.57)	(-0.45)
Public Trans Usage (%)	1.058***	1.056	1.119***	1.034	1.055	1.156***
	(3.72)	(1.71)	(4.57)	(0.98)	(0.80)	(3.77)
Interaction	1.009	1.025*	0.994	1.025	1.000	0.980
	(1.83)	(2.41)	(-0.69)	(1.68)	(0.01)	(-1.22)
PUBLIC TRANSPORTATION TRAVEL - Conditional Duration						
Real Price Gas (\$)	-0.209	-0.0135	0.0210	-0.522*	-0.551	-0.608
	(0.145)	(0.434)	(0.367)	(0.228)	(0.371)	(0.387)
Public Trans Usage (%)	0.00819	-0.272	0.249	-0.0133	0.0455	0.0183
	(0.0255)	(0.176)	(0.157)	(0.0375)	(0.122)	(0.107)
Interaction	0.0654*	0.266**	-0.0293	0.0679*	-0.00458	0.0527
	(0.0267)	(0.0943)	(0.0363)	(0.0293)	(0.0581)	(0.0540)
SELF TRAVEL - Participation						
Real Price Gas (\$)	1.094	1.058	1.497***	0.990	0.996	0.911
	(1.48)	(0.47)	(3.45)	(-0.09)	(-0.02)	(-0.50)
Public Trans Usage (%)	1.057**	1.044	1.156***	1.008	0.995	1.066
	(2.69)	(1.48)	(6.76)	(0.31)	(-0.19)	(1.55)
Interaction	0.998	1.008	0.967***	1.019*	1.017	0.992
	(-0.41)	(0.71)	(-3.93)	(2.19)	(1.56)	(-0.51)
Observations	42795	7418	9796	7151	4898	7500
SELF TRAVEL - Conditional Duration						
Real Price Gas (\$)	0.220	0.757	1.054	-0.904	-0.504	0.650
	(0.345)	(1.224)	(0.772)	(0.529)	(0.528)	(0.595)
Public Trans Usage (%)	0.247	-0.00826	0.791	0.0617	-0.113	0.522*
	(0.159)	(0.310)	(0.486)	(0.106)	(0.150)	(0.243)
Interaction	0.0264	0.333**	-0.175	0.0627	0.118	-0.150
	(0.0362)	(0.121)	(0.156)	(0.0576)	(0.0633)	(0.0907)
Observations	42795	7441	9842	7230	5028	7587

Exponentiated coefficients; t statistics in parentheses

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

Table 3.13: **Effect of Gas Prices and Public Transportation on Travel Time† by Mode**
Without NY, CHI, BOS, SF, DC metros

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
CAR TRAVEL						
Real Price Gas (\$)	-5.069***	-5.550	-1.934	-4.180	-10.76*	-5.102
	(1.135)	(2.785)	(2.475)	(3.969)	(4.379)	(2.978)
Public Trans Usage	-1.220	-3.325*	0.277	0.432	-2.758	-2.817
	(0.730)	(1.269)	(2.130)	(1.843)	(2.191)	(1.518)
Interaction	0.338	0.876	-0.247	-0.706	1.168	1.236
	(0.264)	(0.566)	(0.729)	(0.782)	(0.932)	(0.654)
PUBLIC TRANSPORTATION TRAVEL						
Real Price Gas (\$)	-0.277	-0.482	0.380	-1.052	-0.419	0.853
	(0.404)	(1.335)	(0.584)	(0.598)	(0.687)	(0.871)
Public Trans Usage	-0.0590	-0.615	0.531	-0.362	-0.0198	0.487
	(0.316)	(0.614)	(0.381)	(0.367)	(0.549)	(0.396)
Interaction	0.265	0.787*	0.0716	0.233	0.136	-0.0324
	(0.143)	(0.319)	(0.173)	(0.169)	(0.244)	(0.158)
SELF TRAVEL						
Real Price Gas (\$)	-0.433	-0.139	0.269	-0.673	-0.820	-0.596
	(0.458)	(1.594)	(0.843)	(0.765)	(1.152)	(1.044)
Public Trans Usage	0.0427	-0.242	0.952*	0.254	-0.0344	-0.261
	(0.298)	(0.789)	(0.408)	(0.504)	(1.071)	(0.549)
Interaction	0.299*	0.891*	-0.0000367	0.00815	0.155	0.242
	(0.129)	(0.344)	(0.175)	(0.234)	(0.454)	(0.241)
Observations	35854	6593	8593	6282	4186	5781

Standard errors in parentheses

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

† Travel time is measured in minutes per average day.

Table 3.14: **Effect of Gas Prices and Public Transportation on Travel Time† by Purpose**
Without NY, CHI, BOS, SF, DC metros

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
ALL TRAVEL						
Real Price Gas (\$)	-6.224***	-6.477*	-1.300	-8.015	-9.779	-7.507
	(1.281)	(2.735)	(2.600)	(4.006)	(5.201)	(4.749)
Public Trans Usage	-1.274	-2.116	2.720	-1.827	-2.522	-4.631
	(0.751)	(1.782)	(2.628)	(1.956)	(3.027)	(2.474)
Interaction	0.867**	1.501	-0.733	0.534	1.360	2.406*
	(0.274)	(0.771)	(0.931)	(0.833)	(1.358)	(1.011)
WORK TRAVEL						
Real Price Gas (\$)	-0.421	1.416	-0.765	-0.219	0.279	-0.740
	(0.763)	(1.250)	(1.410)	(1.846)	(2.579)	(1.961)
Public Trans Usage	0.653	1.614	0.584	0.298	0.471	0.752
	(0.532)	(0.879)	(1.020)	(1.172)	(1.411)	(0.745)
Interaction	-0.0522	-0.313	0.109	-0.113	-0.00800	-0.149
	(0.204)	(0.342)	(0.426)	(0.487)	(0.563)	(0.335)
LEISURE TRAVEL						
Real Price Gas (\$)	-4.568***	-6.958**	-0.253	-3.005	-8.507*	-6.804*
	(1.045)	(2.314)	(1.732)	(2.353)	(3.370)	(2.993)
Public Trans Usage	-1.307*	-2.417	1.569	-0.612	-2.493	-3.585*
	(0.630)	(1.366)	(1.641)	(1.277)	(1.645)	(1.408)
Interaction	0.587*	0.923	-0.539	0.187	1.186	1.823**
	(0.238)	(0.555)	(0.634)	(0.604)	(0.713)	(0.577)
OTHER TRAVEL						
Real Price Gas (\$)	-1.235	-0.934	-0.282	-4.791	-1.551	0.0374
	(0.975)	(1.792)	(2.413)	(2.970)	(3.256)	(3.561)
Public Trans Usage	-0.620	-1.314	0.567	-1.513	-0.500	-1.798
	(0.499)	(1.596)	(1.775)	(1.585)	(2.108)	(2.197)
Interaction	0.332	0.890	-0.303	0.459	0.183	0.732
	(0.189)	(0.722)	(0.671)	(0.659)	(0.922)	(0.866)
Observations	35854	6593	8593	6282	4186	5781

Standard errors in parentheses

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

† Travel time is measured in minutes per average day.

Table 3.15: **Effect of Gas Prices and Public Transportation on Travel Time† by Mode With Density Controls**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
CAR TRAVEL						
Real Price Gas (\$)	-4.721***	-2.757	-4.570*	-4.271	-10.20***	-0.733
	(0.898)	(2.869)	(1.845)	(2.882)	(2.867)	(2.255)
Public Trans Usage	-0.966***	-0.865	-2.097**	0.614	-1.455***	-0.915*
	(0.204)	(0.470)	(0.682)	(0.471)	(0.413)	(0.383)
Interaction	0.232***	-0.110	0.636*	-0.522**	0.506**	0.291*
	(0.0609)	(0.181)	(0.294)	(0.187)	(0.151)	(0.137)
Pop. Density	0.519	1.29	1.64	-1.30	1.37	0.458
(,000s per sq. mi.)	(0.417)	(1.07)	(1.16)	(0.859)	(0.989)	(0.868)
PUBLIC TRANSPORTATION TRAVEL						
Real Price Gas (\$)	0.231	0.672	1.763*	-0.755	-1.320*	0.482
	(0.273)	(1.080)	(0.719)	(0.535)	(0.595)	(0.700)
Public Trans Usage	0.351***	-0.156	1.374*	0.204	-0.0941	0.680***
	(0.0851)	(0.273)	(0.516)	(0.127)	(0.255)	(0.110)
Interaction	0.0649	0.405**	-0.263	0.133	0.180	-0.112
	(0.0457)	(0.128)	(0.160)	(0.0825)	(0.100)	(0.0733)
Pop. Density	0.114	0.949*	-0.193	-0.364	-0.419	-0.0336
(,000s per sq. mi.)	(0.185)	(0.363)	(0.176)	(0.212)	(0.349)	(0.146)
SELF TRAVEL						
Real Price Gas (\$)	0.304	1.225	1.593	-1.079	-1.069*	0.789
	(0.341)	(1.320)	(0.862)	(0.627)	(0.488)	(0.706)
Public Trans Usage	0.360	0.0356	1.413*	-0.0429	-0.154	0.780**
	(0.204)	(0.321)	(0.539)	(0.179)	(0.249)	(0.258)
Interaction	0.0152	0.304*	-0.337	0.169	0.163	-0.215*
	(0.0440)	(0.136)	(0.194)	(0.0984)	(0.0881)	(0.0915)
Pop. Density	0.600***	1.88***	0.256	0.0568	0.280	0.0690
(,000s per sq. mi.)	(0.169)	(0.496)	(0.179)	(0.187)	(0.263)	(0.306)
Observations	42014	7324	9657	7076	4943	7457

Standard errors in parentheses

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

† Travel time is measured in minutes per average day.

Table 3.16: **Effect of Gas Prices and Public Transportation on Travel Time† by Purpose With Density Controls**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
ALL TRAVEL						
Real Price Gas (\$)	-4.522***	-2.367	-3.152	-6.131*	-9.835**	-0.247
	(1.031)	(3.200)	(1.967)	(2.628)	(3.652)	(3.462)
Public Trans Usage	-0.149	-0.291	0.195	0.375	-1.112	0.332
	(0.163)	(0.774)	(0.417)	(0.510)	(0.847)	(0.426)
Interaction	0.329***	0.301	0.317	-0.0755	0.727*	0.140
	(0.0934)	(0.357)	(0.195)	(0.175)	(0.300)	(0.245)
Pop. Density	0.702	3.14**	0.610	-0.271	-0.105	0.0442
(,000s per sq. mi.)	(0.487)	(0.986)	(1.44)	(1.25)	(1.37)	(0.643)
WORK TRAVEL						
Real Price Gas (\$)	-0.180	1.239	0.123	0.255	-0.734	-0.718
	(0.469)	(0.825)	(0.917)	(1.373)	(1.815)	(1.287)
Public Trans Usage	0.258*	0.614**	0.358*	0.632**	-0.0889	0.00473
	(0.111)	(0.189)	(0.157)	(0.191)	(0.223)	(0.339)
Interaction	-0.0144	-0.186*	-0.00346	-0.159	0.0836	0.0609
	(0.0556)	(0.0811)	(0.0685)	(0.104)	(0.109)	(0.180)
Pop. Density	0.721**	0.789	0.994*	0.492	0.245	1.46**
(,000s per sq. mi.)	(0.225)	(0.439)	(0.455)	(0.601)	(0.859)	(0.418)
LEISURE TRAVEL						
Real Price Gas (\$)	-3.622***	-4.202*	-2.133	-3.314*	-8.279**	-0.202
	(0.793)	(1.788)	(1.644)	(1.641)	(2.505)	(2.247)
Public Trans Usage	-0.414*	-0.476	-0.147	-0.421	-1.072***	0.0899
	(0.159)	(0.519)	(0.736)	(0.304)	(0.244)	(0.390)
Interaction	0.240***	0.235	0.162	0.107	0.780***	-0.0688
	(0.0633)	(0.235)	(0.346)	(0.150)	(0.139)	(0.215)
Pop. Density	0.314	0.994	0.274	0.431	-1.05	1.18
(,000s per sq. mi.)	(0.196)	(0.787)	(0.538)	(0.691)	(0.860)	(0.782)
OTHER TRAVEL						
Real Price Gas (\$)	-0.721	0.597	-1.142	-3.072	-0.822	0.673
	(0.727)	(2.288)	(1.858)	(1.965)	(1.811)	(2.345)
Public Trans Usage	0.00655	-0.428	-0.0160	0.164	0.0491	0.237
	(0.106)	(0.582)	(0.481)	(0.427)	(0.577)	(0.384)
Interaction	0.104	0.253	0.159	-0.0234	-0.137	0.148
	(0.0631)	(0.252)	(0.222)	(0.193)	(0.197)	(0.173)
Pop. Density	-0.333	1.36*	-0.658	-1.19*	0.702	-2.60*
(,000s per sq. mi.)	(0.370)	(0.626)	(0.881)	(0.461)	(0.961)	(0.974)
Observations	42014	7324	9657	7076	4943	7457

Standard errors in parentheses

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

† Travel time is measured in minutes per average day.

Table 3.17: **Effect of Gas Prices and Public Transportation on Travel Time† by Mode Using Passenger Miles Per Capita**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
CAR TRAVEL						
Real Price Gas (\$)	-4.618***	-2.700	-4.784*	-3.506	-10.88***	-0.735
	(0.826)	(2.896)	(1.894)	(3.103)	(2.898)	(2.279)
Pass. Miles per cap.	-0.0202**	-0.0139	-0.0429	0.0180	-0.0358***	-0.0191
	(0.00667)	(0.0120)	(0.0225)	(0.0131)	(0.00980)	(0.0104)
Interaction	0.00566**	-0.00327	0.0150	-0.0152**	0.0144**	0.00723
	(0.00195)	(0.00521)	(0.00878)	(0.00548)	(0.00435)	(0.00408)
PUBLIC TRANSPORTATION TRAVEL						
Real Price Gas (\$)	0.0325	0.166	1.616	-0.776	-1.143	0.438
	(0.290)	(1.123)	(0.805)	(0.575)	(0.645)	(0.678)
Pass. Miles per cap.	0.00742**	-0.00536	0.0299*	0.00327	-0.00170	0.0158***
	(0.00244)	(0.00811)	(0.0144)	(0.00348)	(0.00683)	(0.00303)
Interaction	0.00204	0.0116**	-0.00591	0.00317	0.00418	-0.00265
	(0.00126)	(0.00367)	(0.00405)	(0.00236)	(0.00276)	(0.00193)
SELF TRAVEL						
Real Price Gas (\$)	0.0332	0.508	1.302	-1.242	-1.179*	0.673
	(0.366)	(1.358)	(0.945)	(0.715)	(0.501)	(0.714)
Pass. Miles per cap.	0.00888	0.00175	0.0324*	-0.00115	-0.00312	0.0185*
	(0.00512)	(0.0104)	(0.0149)	(0.00501)	(0.00563)	(0.00705)
Interaction	0.000970	0.00977*	-0.00769	0.00396	0.00435	-0.00495
	(0.00109)	(0.00431)	(0.00489)	(0.00286)	(0.00221)	(0.00250)
Observations	42795	7441	9842	7230	5028	7587

Standard errors in parentheses

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

† Travel time is measured in minutes per average day.

Table 3.18: **Effect of Gas Prices and Public Transportation on Travel Time† by Purpose Using Passenger Miles Per Capita**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
ALL TRAVEL						
Real Price Gas (\$)	-4.477***	-3.044	-3.526	-5.399	-9.847*	0.267
	(0.959)	(3.013)	(2.007)	(2.925)	(3.674)	(3.467)
Pass. Miles per cap.	-0.00102	-0.000518	0.00643	0.0158	-0.0268	0.0104
	(0.00377)	(0.0190)	(0.0127)	(0.0138)	(0.0189)	(0.0131)
Interaction	0.00813**	0.00952	0.00738	-0.00511	0.0180*	0.00343
	(0.00269)	(0.00883)	(0.00566)	(0.00571)	(0.00757)	(0.00713)
WORK TRAVEL						
Real Price Gas (\$)	-0.342	1.172	-0.355	0.0997	-0.839	-0.530
	(0.483)	(0.860)	(1.022)	(1.349)	(1.807)	(1.436)
Pass. Miles per cap.	0.00843**	0.0187***	0.0115**	0.0162***	-0.000720	0.00458
	(0.00244)	(0.00479)	(0.00411)	(0.00412)	(0.00720)	(0.00819)
Interaction	-0.0000908	-0.00503*	-0.000136	-0.00330	0.00230	0.00160
	(0.00138)	(0.00202)	(0.00198)	(0.00227)	(0.00339)	(0.00446)
LEISURE TRAVEL						
Real Price Gas (\$)	-3.524***	-4.554*	-1.920	-3.021	-8.112**	-0.211
	(0.761)	(1.773)	(1.579)	(1.738)	(2.539)	(2.330)
Pass. Miles per cap.	-0.0101**	-0.0120	-0.00321	-0.00642	-0.0321***	0.00442
	(0.00373)	(0.0145)	(0.0186)	(0.00901)	(0.00772)	(0.0118)
Interaction	0.00621***	0.00750	0.00400	0.00113	0.0200***	-0.000988
	(0.00144)	(0.00649)	(0.00847)	(0.00467)	(0.00497)	(0.00610)
OTHER TRAVEL						
Real Price Gas (\$)	-0.611	0.338	-1.250	-2.478	-0.896	1.008
	(0.776)	(2.246)	(1.808)	(2.157)	(1.963)	(2.385)
Pass. Miles per cap.	0.000617	-0.00725	-0.00191	0.00600	0.00604	0.00140
	(0.00372)	(0.0153)	(0.0111)	(0.0108)	(0.0129)	(0.0120)
Interaction	0.00200	0.00706	0.00352	-0.00295	-0.00435	0.00282
	(0.00207)	(0.00651)	(0.00539)	(0.00485)	(0.00510)	(0.00526)
Observations	42716	7429	9821	7218	5023	7579

Standard errors in parentheses

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

† Travel time is measured in minutes per average day.

Table 3.19: **Effect of Gas Prices and Public Transportation on Travel Time† by Mode Using Operating Expenses Per Capita**

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
CAR TRAVEL						
Real Price Gas (\$)	-4.798***	-2.975	-5.058*	-2.837	-10.96***	-1.355
	(0.879)	(3.110)	(2.362)	(3.502)	(3.115)	(2.402)
Op. Expenses per cap.	-0.0365*	-0.0318	-0.0746	0.0315	-0.0593**	-0.0385
	(0.0158)	(0.0239)	(0.0488)	(0.0279)	(0.0214)	(0.0216)
Interaction	0.00983*	-0.00330	0.0245	-0.0283*	0.0227*	0.0148
	(0.00476)	(0.0105)	(0.0198)	(0.0116)	(0.00995)	(0.00824)
PUBLIC TRANSPORTATION TRAVEL						
Real Price Gas (\$)	-0.00303	-0.269	1.794	-0.803	-1.367	0.757
	(0.297)	(1.178)	(0.986)	(0.655)	(0.743)	(0.680)
Op. Expenses per cap.	0.0136*	-0.00903	0.0531	0.00707	-0.00639	0.0310***
	(0.00591)	(0.0171)	(0.0293)	(0.00651)	(0.0110)	(0.00668)
Interaction	0.00354	0.0216**	-0.0101	0.00508	0.00791	-0.00579
	(0.00215)	(0.00745)	(0.00803)	(0.00450)	(0.00475)	(0.00351)
SELF TRAVEL						
Real Price Gas (\$)	0.0405	0.0694	1.575	-1.162	-1.425*	0.848
	(0.404)	(1.417)	(1.111)	(0.870)	(0.552)	(0.828)
Op. Expenses per cap.	0.0165	0.00356	0.0585	0.00201	-0.00790	0.0329*
	(0.0109)	(0.0206)	(0.0297)	(0.0107)	(0.0104)	(0.0150)
Interaction	0.00160	0.0189*	-0.0135	0.00551	0.00835	-0.00871
	(0.00220)	(0.00797)	(0.00940)	(0.00601)	(0.00419)	(0.00523)
Observations	42716	7429	9821	7218	5023	7579

Standard errors in parentheses

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

† Travel time is measured in minutes per average day.

Table 3.20:
Effect of Gas Prices and Public Transportation on Travel Time† by Purpose Using Operating Expenses Per Capita

	ALL	\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
ALL TRAVEL						
Real Price Gas (\$)	-4.602***	-3.230	-3.484	-5.303	-10.13*	-0.194
	(1.033)	(3.077)	(2.117)	(3.251)	(3.915)	(3.716)
Op. Expenses per cap.	-0.000320	0.00301	0.0144	0.0251	-0.0476	0.0147
	(0.00788)	(0.0371)	(0.0245)	(0.0284)	(0.0355)	(0.0283)
Interaction	0.0136*	0.0165	0.0110	-0.00853	0.0296	0.00830
	(0.00575)	(0.0170)	(0.0118)	(0.0115)	(0.0157)	(0.0146)
WORK TRAVEL						
Real Price Gas (\$)	-0.247	1.434	-0.274	0.391	-0.898	-0.544
	(0.510)	(0.910)	(1.110)	(1.403)	(1.866)	(1.611)
Op. Expenses per cap.	0.0157**	0.0351***	0.0217*	0.0317**	-0.00224	0.00722
	(0.00584)	(0.00872)	(0.00924)	(0.00976)	(0.0126)	(0.0166)
Interaction	-0.000731	-0.00952*	-0.000722	-0.00702	0.00392	0.00262
	(0.00283)	(0.00362)	(0.00463)	(0.00505)	(0.00575)	(0.00823)
LEISURE TRAVEL						
Real Price Gas (\$)	-3.777***	-5.157*	-1.395	-2.877	-8.666**	-0.702
	(0.788)	(1.969)	(1.758)	(1.899)	(2.789)	(2.461)
Op. Expenses per cap.	-0.0184*	-0.0263	0.00470	-0.00885	-0.0582**	0.00319
	(0.00719)	(0.0301)	(0.0361)	(0.0197)	(0.0177)	(0.0226)
Interaction	0.0114***	0.0163	0.00211	0.000574	0.0346**	0.00131
	(0.00269)	(0.0130)	(0.0164)	(0.00954)	(0.0117)	(0.0114)
OTHER TRAVEL						
Real Price Gas (\$)	-0.579	0.493	-1.815	-2.816	-0.568	1.053
	(0.865)	(2.526)	(1.937)	(2.346)	(2.120)	(2.725)
Op. Expenses per cap.	0.00236	-0.00571	-0.0119	0.00232	0.0128	0.00433
	(0.00734)	(0.0317)	(0.0227)	(0.0216)	(0.0234)	(0.0260)
Interaction	0.00293	0.00974	0.00960	-0.00209	-0.00892	0.00436
	(0.00417)	(0.0141)	(0.0108)	(0.00944)	(0.00935)	(0.0115)
Observations	42716	7429	9821	7218	5023	7579

Standard errors in parentheses

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

† Travel time is measured in minutes per average day.

Table 3.21: **Yearly Welfare Incidence of a 25 cent increase in real gas prices**

ACS Metro Area PT Usage		\$0-\$25K	\$25-\$50K	\$50-\$75K	\$75K-\$100K	\$100K+
0.0%	Welfare Loss (\$)	102.95	134.67	127.57	141.83	153.08
	WL/Income	0.82%	0.35%	0.20%	0.16%	0.10%
2.5%	Incidence (\$)	100.28	127. 53	129.36	136.80	149.59
	WL/Income	0.80%	0.34%	0.21%	0.16%	0.10%
5.0%	Incidence (\$)	97.61	120.59	131.15	131.77	146.41
	WL/Income	0.78%	0.32%	0.21%	0.15%	0.10%
10.0%	Incidence (\$)	102.95	106.51	134.73	121.72	139.72
	WL/Income	0.82%	0.28%	0.22%	0.14%	0.09%
Observations	7410	9785	7142	4872	7480	

Welfare Loss measured in (dollars) lost per year from a base price of \$2.50 per gallon.
Loss to Income ratio is measured at the midpoint income of each bin and \$150K for the last bin.

CHAPTER IV

Employment and Intra-household Time Allocation

4.1 Introduction

The loss of employment by one partner in a dual-headed household has numerous effects on the well-being of both parties. The loss of income can lead to a reduction in consumption for the entire household, and both individuals must reorganize the time usage of the household. No longer does the employed partner have several hours of each day devoted to paid work activity, and thus he or she must spend time on other activities such as more leisure or more household production if market work is no longer an option. The other spouse may feel the need to work more to make up for the loss income of the other spouse and may be able to spend less time in household production, depending on the time use of the unemployed partner. Alternatively more overall household production time may be needed as the household shifts towards more time intensive production activities.

The paper examines the effect of unemployment on the time use patterns of both partners in a household, with separate effects calculated for each sex and for weekday and weekend time use. I utilize multiple empirical specifications and construct predictions for the time use of unsurveyed partners to determine marginal effects using the American Time Use Survey (ATUS). Across most specifications, I find consistent estimates that females respond to partner unemployment by working 80-90 minutes per week more, with only small changes to leisure. Household production, however, declines by about 2 hours per week. Males respond similarly, taking on about 50-70 minutes per week. Own work time declines by about 32-35 hours per week for women and 36-39 hours a week for men. Additional household production is the result of one-half to two-thirds of this time for women and about one-third to one-half of this time for men. Adding income as controls has minimal effect on the average estimates, but there is indication that the effect of partner's unemployment differs by income. I also attempt to estimate the effect of a change in a partner's employment status on own time use but find only small responses for both sexes.

The economic significance of examining the effect of unemployment on time use is shown in two related strains of literature that examine household dynamics. When an income-producing member of a household loses his or her job, the family is then tasked with identifying alternate ways to meet the expenditure needs of its members. If an alternate job cannot be procured, a utility-maximizing household, in the traditional neo-classical framework such as first described in Becker (1965), have a variety of options from which they can draw. They may choose to utilize existing savings or borrow against future earnings, they can reduce expenditures by changing leisure choices or identifying more time-intensive means of household production, or other household members can seek to increase their own labor supply.

This was detailed more broadly by Gronau (1977) who sought to emphasize the importance of treating home production and home leisure separately from each other. Consumption is modeled to be a combination of goods and services and time spent consuming them, but the goods and services themselves can be either produced with home production time or purchased in the market using income derived from time spent in market work. In this context, home production and market work are substitutes for each other since they both generate the goods and services which are complementary to leisure time.

A question that still remains however is how consumption and time use decisions are tied together within households. The literature examining the effect of unemployment on a household has mainly focused on labor supply models, with the predicted resulting positive impact on spousal work hours being termed the "Added Worker Effect". The concept is important because such behavioral changes allow a household to self-insure against unemployment in addition to public unemployment insurance (Ashenfelter, 1980; Heckman and MaCurdy, 1980, 1982; Lundberg, 1985; Cullen and Gruber, 2000). Evidence for an Added Worker Effect was usually found to be existent but quite small and many times not statistically different from zero (Spletzer, 1997). Cullen and Gruber (2000) noted that unemployment insurance itself was found to crowd out increases in spousal labor supply and Bingley and Walker (2001) found similar evidence examining UK unemployment insurance programs. Those authors found means-based unemployment benefits based on household income reduced the labor supply of women with unemployed husbands. Related, Krueger and Mueller (2010) find that time spent on job search activities declines with benefit generosity and increases as benefits are set to expire utilizing the time use data used in this paper, and Güler and Taskin (2013) find that home production time falls with increases in unemployment benefits.

The implication for many of these studies is that when considering the reduction in household production and increases in spousal labor supply that result from unemployment benefits, said benefits crowd out these alternative household methods of insuring against welfare losses due to unemployment. However, the economic indications of whether household production is a substitute for market work is still questionable. Using American data, Burda and Hamermesh (2010) find increases in household production generated by unemployment were between one-eighth and one-half the reduction in market work time in Italy, Australia and Germany; for America, this ratio was about 31%. Cyclical unemployment, however, is more likely to result in higher household production than long-term. Most recently, Aguiar et al. (2011) use ATUS data during the recent recession to determine how lost work hours were allocated, identifying 30-40% are spent on increases in household production.

There have also been a series of papers examining the effect of macroeconomic unemployment on time use as well as evidence these effects can be dramatically different depending on the culture or country. A paper utilizing the Spanish Time Use Survey by Gimenez-Nadal et al. (2010) sought to determine the impact of unemployment on household production as well as how the regional unemployment situation helped shaped that impact. They found only a small, but significant portion of time that would have otherwise been spent working is spent on household production (about 20%) with the majority devoted to leisure time. Their larger contribution however was identifying evidence that higher unemployment rates coincide with increase levels of household production for the unemployed. Ahn et al. (2005) find even larger effects of own-unemployment on home production. Conversely, Lee et al. (2011) find little effect on reduced hours worked on increased household production, however they were examining exogenous reductions in market work generated by legal reductions in the work week in Japan and Korea.

Most of these papers, however, only examine time use behavior of a single respondent. In this paper, I seek to examine the combination of the added worker effect as well as the intra-household effects (if any) that an increase in household production might arise. Note, household production resulting from lower income does not necessarily result in it being performed by the unemployed; while production occurring because unemployment reduces opportunity costs, prior specialization still might be a factor in potential increases. The effect of unemployment on spousal time use then is an interesting and theoretically and empirically ambiguous question which informs the general question of the substitutability of household production and market work.

Much of the past work on household labor supply has examined the effect of relative wages on intra-household bargaining over consumption and time use, examining tests of unitary vs. collective models of household labor supply (Fortin and Lacroix, 1997; Chiappori et al., 2002; Blundell et al., 2007). Most find difficulty reconciling the unitary model with strong empirical data suggesting some bargaining and autonomy in decision making separate from the household. They also find increasing bargaining positions can increase women's labor supply (and vice versa). Bloemen et al. (2010) examine Italian couples using dual surveys and identify education levels of both the mother and father positively affect the time spent with children for the father, and trends change significantly between weekend and weekday. Child care and household production in general is larger with younger child presence.

Using time use data in particular has grown in recent years as the American Time Use Survey (ATUS) has aged and collected more waves. Friedberg and Webb (2006) estimate similar aspects of bargaining and use changes in time use to test bargaining models based on the effect of spousal relative wages. Utilizing leisure time as a measure of utility, they find higher relative wages for women result in more time spent in leisure and less time in household production. Such bargaining effects, they also conclude, are largest for childless couples, where gains are potentially greater due to less demand for household production. Bittman et al. (2003) found similar effects in Australian data, but only when the male-to-female wage ratio was greater than one and Daunfeldt and Hellström (2007) use Swedish data to examine the determinants of participation in different household activities, identifying wages and age as significant predictors.

The empirical part of this paper has two parts, one which estimates the effect of own and partner employment status on time use and a second which uses a synthetic measure of spousal time use to determine the marginal effects of changes in spousal time use on own time use. A large increase in unallocated hours due to unemployment is likely to be divided primarily between leisure and household production and it is an open empirical question as to how much of each will be allocated. For partner unemployment, own time use in work may increase due to the added worker effect and it is possible partner's increase in household production may allow for a decline in their own production. Income effects, however, may necessitate an increase in time-intensive household production which could even increase own time in such activities; therefore, the expected change in household production for partner unemployment is unclear.

The estimation of marginal effects necessitates a different discussion on expectation of changes. The estimation here specifically omits the joint decision, and without actual data on spousal time use, this may not be possible anyway. The estimation procedure below looks at the changes in own time use as if the spousal time use were independent. While this is a very strong assumption, the use of artificial data allows the measurement of average changes to such behavior with fewer concerns about endogeneity. Admittedly, some, if not most, of the measured effect will be from not a direct response to a change in spousal time use, but rather reflect the totality of the joint household and individual utility maximization decisions as they are averaged across the population.

If there is an added worker effect, it is unclear how that marginal increase work time would have an effect on other time uses. There may be an increase in leisure activity and a decrease in household production as the household shifts to more more costly, less time-intensive household production (relative to no change in spousal work time) or such work time could be taken from the sleep and personal maintenance time with no change in spousal or even household leisure or household production time. One could expect an added worker effect would be larger for those with higher incomes who may have more flexibility in their choice of work hours, but due to the income effect, they may not necessarily have as much need for the higher income. Indeed, I find some empirical evidence both of these could be true resulting in U-shaped curve of estimates of the added worker with respect to income for males.

An increase in spousal leisure time may lead to an increase in own leisure time if there exists complementarities, which has been suggested based on the findings of Hamermesh (2002); Hamermesh et al. (2008). It is unclear what would be the effect of an increase in marginal spousal household production as a priori, it is unclear whether such activity is a net substitute for own household production or if there exists complementarities such as when a couple washes dishes together. If it is a new substitute, then we would expect a possible increase in either own leisure or work time.

4.2 Data

To explore the impact of unemployment on household time use, I utilize the American Time Use Survey (ATUS) from 2003-2010. Each respondent of the ATUS is informed of an upcoming day during which they are asked to keep a time diary of each activity they perform, its duration and location and whomever the respondent was with at the time. The sample is drawn from outgoing Current Population Survey (CPS) cohorts, which allow researchers to match ATUS and CPS data. Only one adult from each household is asked to respond, however, so interviews for both partners in a couple are not available. For the time period I analyze, there were 112,038 diaries recorded; of these, 60,217 respondents reported a cohabiting partner for which CPS and ATUS survey data were available.

The sample was nationally representative but stratified by day of the week, with roughly a quarter of the sample diaries taken for Saturday and Sunday each and a tenth of the sample for each weekday. The BLS provides survey files that include the amount of total time each respondent spends in each activity. In addition, ATUS provides a variety of demographic and household information collected at the time of the survey as well as many reported from the final month of the CPS. Own employment at the time of the survey is recoded to Employed, Unemployed or Not in the Labor Force[1]. Spousal unemployment is more difficult to ascertain as the ATUS does not ask questions that differentiate between those with partners who are unemployed but still in the labor force and those not in the labor force. Unemployment was constructed by coding those partners who reported either being employed or unemployed (in the labor force) during the CPS-8 interview 2-6 months prior AND coded as not employed in the ATUS. This has the potential of casting a wider net as it would also include those not in the labor force. As such, unemployment rates for partners are much higher than for the diary respondents. Those who were not in the labor force and are now unemployed are considered to still be not in the

[1] Employed is divided into actively working and employed but absent from work and Unemployed is split between those who are without a job or laid off from a job with likely expectation of rehire. These are collapsed to compare with the spousal group for which this division is not recorded.

labor force for my purposes. The reasoning behind this choice was that this group did not experience a change in employment status that would affect household time use.

Each of the following analyses is performed separately for male and female and for weekday and weekend. Summary sample demographic statistics are reported for the population in Tables **??** and 4.2. Summary statistics grouped by income category are reported in Tables 4.3 and 4.4. Males are more likely to be employed full time and women are more likely to be employed part time. In addition to differences in employment, there are substantial differences of demographic characteristics by income level. Income is negatively correlated with the likelihood of being black, hispanic or living in a non-metropolitan area. This could be provide evidence omitted variable bias may be a concern. If the physical size of a household's residence affects leisure and household production choices, this would introduce bias in the estimates of coefficients of variables which are correlated. It is unclear which direction overall omitted variable bias would be for each variable, but it is a potential source of concern with the data.

I aggregate the time use data into three categories, consisting of Work[2], Leisure[3] and Household Production[4]. Activities types which do not fall into these categories include personal care, education and time spent traveling or on the telephone[5]. The type of activity recorded is based on the primary activity in which the respondent

[2]ATUS code 05 consisting of time spent on work, income-generating activities and job search activities

[3]ATUS codes 12-15 consisting of Socialising, any leisure activity, sports and exercise, religious activity and volunteer activity.

[4]ATUS codes 2-4 and 7-10, consisting of household maintenance, care for household and non-household members, and time spent shopping and or acquiring professional, personal, household and government services

[5]Transportation and some telephone activities are considered activities which can be performed in service of another activity. While an argument could be made for including them as part of the total amount of time devoted to work, leisure and household production, I choose not to. This reflects a desire for the activity times to reflect the time devoted specifically towards the income generation, utility generation or time-money transformation that these three activities represent.

reports participating.[6] As such, the ATUS will under-report such activities[7].

Tables 4.5 and 4.6 show the mean average times spent in each category as well as the proportion of the sample whom participated in any activity within those categories. It is unsurprising that respondents in households with higher incomes work more on average, but the timing of household production is very different based on income. Weekday household production declines with income, while weekend household production increases with income. This may be due to higher degrees of market-substitution for household production which occurs on weekdays versus weekends.

Abraham et al. (2006) detail other issues involved with data collection for the ATUS citing the length and burden of the survey. They suggest non-response bias could be introduced if those who respond to the survey have time habits which differ from respondents. For example, ATUS respondents were much more likely to be volunteers based on linking them back to a CPS Volunteer Supplement. In addition, ATUS is exclusively a computer assisted telephone interview survey, given after participation in the CPS. This increases the difficulty in reaching respondents, and unlike the CPS, a specific member of the household is selected for response. Respondents who are unemployed, less educated, young, Hispanic and black all have lower response rates, primarily though lower contact rates. As such, the ATUS sample will have an unemployment rate that is lower than the population rate at large. While I do not correct for that source of bias, results of any study using ATUS data should be interpreted with this in mind.

Additionally, there is a history of worry about the quality of labor statistics with

[6] For example, if a person is reading articles online with a laptop while also watching television, only one activity, whichever the respondent states as primary, will be recorded. Listening to the radio or music is known to be chronically underreported since the vast majority of such activity is performed as a secondary activity.

[7] Although I am not making use of this aspect of the data, one noteworthy exception is that the ATUS interviewer will specifically ask and record secondary activities as they relate to child-care where appropriate.

regards to their ability to capture the underground economy[8], there is no present validation study regarding the accuracy of the self-reported time use diaries. It should be noted that while ATUS interviewers do not ask questions related to the specifics of income-producing activities, they do probe respondents when they are unclear as to if a respondent is being paid for an activity or not as well as ask for the location of all activities. That said, the vast majority of the time reported in the Work category for the unemployed consists of job-search activities[9], indicating respondents who are truthfully reporting their time use activities with substantial income-producing time in underground activities are properly coded as part-time or full-time workers. If respondents are purposefully misreporting income producing activities as other types of time use such as sleeping, leisure, or household production, this could bias the estimates of the effect of unemployment on those activities. This is particularly so, if they choose a time use mix that is substantially different from the activities of actual non-working unemployed respondents. Note the error here is not a misreporting of what unemployed people do, but a misclassification of the respondent as unemployed. That said, as these respondents have been primed through several rounds of CPS questions and have continued to participate in the ATUS, it seems unlikely this would be a substantial source of error in the data.

4.3 Empirical Estimation

4.3.1 Effect of Spousal Employment Status

I perform two different estimations to calculate the interaction of spousal employment on household time use. I first use an OLS estimation of the following equation:

$$T_i = \beta_0 + \beta_1 FTE_i + \beta_2 PTE_i + \beta_3 UN_i + \beta_4 FTE_{Pi} + \beta_5 PTE_{Pi} + \beta_6 UN_{Pi} +$$

[8] Gutmann (1978) and McDonald (1984) provide early examples of attacks and defenses of the data on these grounds

[9] The mean time in Work activities for all unemployed respondents with partners is 29.9 minutes per day and the mean time in job search activities for the same group is 23.3 minutes per day.

$$\gamma_1 X_i + \gamma_2 X_{Pi} + \gamma_3 H_i + \gamma_4 T_i, \tag{4.1}$$

where FTE, PTE and UN represent indicators for full-time employment, part-time employment and unemployment for the respondent and their partner. Each coefficient estimate is thus calculated relative to those not in the labor force. X and X_p are individual characteristics of the respondent and partner including age, age squared, education and indicators for black and hispanic. H_i includes household level characteristics of the presence of any children, a child under the age of 5 and a child under the age of 10 as well as the state and metropolitan status of the household. T_i includes several controls for the date of the diary: the day, week, month and year of the survey and an indicator if the day of the survey was a holiday. The time and location based regressors along with race and education characteristics are unreported in the following regression results.

When confronted with data that include a large number of zero points or where the dependent variables are otherwise limited in some manner, the Tobit statistical model is frequently employed to model the underlying relationships. This is the procedure by which Connelly and Kimmel (2009b) use to construct their estimates of spousal time use in a Seemingly Unrelated Regression model. The Tobit specification, however, assumes the likelihood of participating in an activity and the amount of time spent in an activity are the result of the same underlying decision process (Stewart, 2009) This is unlikely to be true for time use in a number of cases. As Stewart (2009) explains, where there are large numbers of non-participation, Tobit performs poorly relative to OLS in generating unbiased and consistent results. The authors also found that OLS performs well, but might still be problematic since a linear specification permits prediction of time use that are negative, which is not possible.

Using Swedish data, Daunfeldt and Hellström (2007) come to a similar conclusion and utilize a Cragg model to estimate the determinants of time use for various household production activities. The empirical strategy developed in Cragg (1971) appears to be a theoretically nice fit for time use data. Instead of a regressor forced to have the same directional affect on the probability of participation and the duration of activity, the Cragg model separately models both decisions Burke (2009). In particular, the model combines a probit with the truncated normal when the variable of interest t is positive:

$$f(s,t|\boldsymbol{x_1}\boldsymbol{x_2}) = \{1-\Phi(\boldsymbol{x_1}\gamma)\}^{I(w=0)}[\Phi(\boldsymbol{x_1}\gamma)(2\pi)^{-\frac{1}{2}}\sigma^{-1} \tag{4.2}$$

$$exp\{-(y-\boldsymbol{x_2}\beta)^2/2\sigma^2\}/\Phi(\boldsymbol{x_2}\beta/\sigma)]^{I(w=1)}$$

where s is an indicator equal to 1 if t is positive and 0 otherwise. In the above model, γ is the vector by which x_1 affects the probability of participation and β is the vector by which x_2 affects the amount of time spent in an activity. Of note, if $x_1 = x_2$ and $\gamma = \beta/\sigma$, then this is equivalent to the Tobit model (Burke, 2009; Cragg, 1971). Using the same covariates, I thus perform this two-part Cragg estimation that separately estimates the participation and time length decisions.

Since a continuous income variable is not readily available for the respondents, I repeat each of the above regressions by including income controls based on income categories which are provided for about 90% of the sample in the ATUS data[10]. Coefficient estimates are reported relative to those making between \$0 and \$30,000. Additionally, both the OLS and Cragg estimations are run on each income category subsample separately to determine if there is a differential impact on each of the coefficient estimates.

[10] These categories are classified by \$0-\$30,000, \$30,000-\$50,000, \$50,000-\$75,000, \$75,000-\$100,000 and above \$100,000

Table 4.7 presents the difference between the coefficients of full employment and unemployment (reported in weekly hours) for both respondents and partners for each of the respondent time use values. Table 4.8 present the same estimates when income controls are utilized. Full estimation results for the OLS regressions, with and without income controls, are found in Tables 4.9 - 4.12. Tables 4.13 - 4.16 report the Cragg estimates of the effect on unconditional time use. These are calculated by generating predicted values for the sample and then calculating the marginal effects on the probability of activity participation and on the amount of reported activity time conditional on activity participation. The product of these two values gives the marginal effect on the unconditional activity time. Bootstrapped standard errors are reported.

A loss in employment leads to 32-35 less hours of work per week for women and 36-39 hours less work per week for men when looking at the OLS and Cragg estimations, which are roughly consistent with expectations, providing some validity to the empirical strategy. We see larger own-unemployment reductions in work time for men, as expected because they spent more time in work on average. With this increase in available time, about two-thirds to one-half is spent in household production for women and one-half to one-third for men. This provides evidence that unemployment does not lead to all extra time sleeping and watching television, although the remainder of the time is mostly spent in leisure activities. Additionally, such values are consistent with those found in Aguiar et al. (2011).

The impact of a change in employment by a respondent's spouse has a small, but statistically significant impact on labor supply of about an hour and half increase for females and about an hour for males per week. This is entirely consistent with previous literature on the Added Worker Effect. This effect is larger for women than men which may reflect higher flexibility for labor supply choice or a higher need for the household to replace the earnings of a male partner. These regressions include the sex of the partner, and tables 4.9-4.15 do seem to suggest those with male partners work less on weekdays for both sexes.

It is quite likely that a reduction of 2-3 hours per week of household work due to partner unemployment for both men and women does allow for this increased labor supply. As the amount of household production reduced by respondents whose partner is unemployed is much smaller than the increase by the unemployed respondents, it is likely that this extra production represents new household work as opposed to purely taking on the partner's responsibilities. This indicates either a substitution of household production for income from market work or a shift of household production time from the future for larger prospects that are not related to normal daily or weekly maintenance. There is little evidence of any noticeable impact of a partner's unemployment on leisure time.

Of note, the existence of children significantly increases the amount of household production and decreases leisure time for both sexes on weekdays and weekends. Changes are much smaller for men than women, however; having a child under the age of 5 increases household production time by 16.6 hours weekly for females and by 9.0 hours weekly for males [11]. Similarly, leisure time is reduced by 8.5 hours for women and only 5.6 hours for men. Work time does not significantly change much except for mothers of children under the age of 5 on weekdays. Additionally, women with same sex partners work considerably more (7.0 hours a week) with most of that time (6.1 hours) coming from a reduction in household production. Males in same sex couples have the opposite direction, working less and spending more time in

[11] Calculated by adding the three children-related coefficients 5 times for weekeday and 2 times for weekend and then dividing by 60

household production, however the effects are smaller and not statistically significant. Marginal effects from the Cragg estimation are similar, generating less leisure for more household production during weekdays for females and more reduction of leisure for males.

The addition of income controls does not substantially change the estimates of the coefficients from the estimation procedures or the difference between full-time employment and unemployment. There is some small indication it increases the measure of the added worker effect, particularly for men. This may be due to male partner unemployment occurring more likely in households at income levels which see lower added worker effects. Differences generated by income could be a result of either differences in the desire for more spousal work time or differences in the ability to obtain more spousal work time. I explore these potential differences by performing an OLS estimation separately for each income level[12]. Calculated estimates of the time use effects of full employment to unemployment are plotted in Figure 4.1. Bars indicating 95% confidence intervals are included.

There does not appear to be substantial variation across income levels with respect to time use changes resulting from own unemployment, except for a couple key observations. Females of higher incomes report more of their time in household production and less in leisure than those of lower incomes. This may be the result of those households substituting market-based household production for one's own. This is consistent with the idea that higher income households would be more likely to obtain market-based household production. Interestingly, this observation does not seem to be generated for men indicating women are more likely to peform this substitution as a result of unemployment than man are.

[12]Note the sample size is now being split three ways (by gender, weekday/weekend and income), in addition to losing about 12% of the sample through omitted income. Each regression only includes about 2500-3000 observations. As such, the Cragg estimation procedure fails to converge for several of the subsamples.

The impact of partner's unemployment does seem to generate an added worker effect that differs across income levels. The point estimate for females in households reporting income over $100,000 is double that of those making below $75,000. Sample sizes generate standard errors which are too large to confirm a statistical significance, but this would seem to be an economically significant difference. Females in this income group also experience more household production less of a decline in household production than those making less. While the added worker effect is smaller for men, there is also an indication that the added worker effect for males also increases with income, although there is also an increase for those making less than $30,000 as well. This would be consistent with the idea that partners of the unemployed in households with high levels of income are more likely to either want to or be able to work more hours. Male workers in poor households are also more likely to illustrate an added worker effect compared to those in middle-income households, while this difference does not seem to be illustrated for females. Males in poor households also exhibit substantially less household production relative to the rest of the population.

4.3.2 Marginal Effect of Spousal Time Use

With the results of the estimation procedure above, it is then possible to construct out-of-sample predictions of spousal hours in each of the three activities of work, leisure and household production. These constructions are necessary because the ATUS asks of a diary from only one selected member of a household. From this, I estimate the average and marginal effect an additional minute of partner activity has on one's own activity.

Connelly and Kimmel (2009a) discuss the fatality of not having dual diaries from a household. Using their model from Connelly and Kimmel (2009c) of the effect of relative wages on spousal time and child care, they jointly estimate time use using in-sample respondents for the out-of-sample spouses. Additionally, they use a propensity score matching system to "marry" two respondents with characteristics similar to each others' spouses. Using German data that include spousal diaries, they evaluate the usefulness of each approach, determining that there are costs and benefits in the constructed or matched data versus actual data (which do not exist for ATUS). Matching models generate more variation and can lead to fewer significant results and different results that predicted or actual data, although they argue the ATUS matches are of higher quality than the tested German data. Predicted out-of sample constructions generate results which are also less significant than actual data, but are generally consistent. They also note that actual spousal data is not necessarily the best option because of the endogeneity in jointly-considered household time choices and possible preferences for (or against) coordination, depending on the questions being asked. The estimate using the propensity score matching procedure, however, would seem highly dependent on the choice of matching procedure. Connelly and Kimmel (2009c) predict the gender of the spouse, but do not indicate why matching on "male-ness" would be the best suited variable of interest.

I do construct out-of-sample spousal time use by utilizing the previous Cragg estimation results (without the income indicators) to then estimate the probability of participation for spousal activity, the expected value of time conditional on activity participation from the truncated regression and then multiply the two to generate an estimate of the unconditional time use in work, leisure and household production for each spouse. The process generates means for the predictions of spousal time use which are very close to those of the sample itself.

Again, I perform an OLS regression and and a two-part Cragg estimation on the sample with the constructed spousal time use to estimate the marginal effect of spousal time use. Endogeneity with the time use of the respondent may still a factor, but because these are constructed, out-of-sample time uses, concerns should be minimal. The OLS is of the form:

$$T_i = \beta_0 + \beta_1 FTE_i + \beta_2 PTE_i + \beta_3 UN_i + \beta_4 \widehat{Work}_{Pi} + \beta_5 \widehat{Leisure}Pi +$$
$$\beta_6 \widehat{HHProd}Pi + \gamma_1 X_i + \gamma_2 X_{Pi} + \gamma_3 H_i + \gamma_4 T_i, \tag{4.3}$$

with the two-part Cragg estimation using the same covariates.

Tables 4.17 and 4.18 present a summary of the regressions reporting just the coefficient estimates for spousal time use from for each of the three own-time uses. Results are presented in minutes changed by the respondent per one hour change in spousal time. The magnitudes generated by the OLS and Cragg estimations are slightly high relative to the results from the first part, but most are consistently signed. The marginal effects are all of the same sign as the effects seen in Table 4.7. The magnitudes calculated using the OLS regression from the Cragg estimates are likely unreasonably high, but may be plausible if marginal activity is more likely to be dependent on spousal behavior.

Full results from the OLS regressions using the Cragg estimators are found in Tables 4.19 and 4.20. Results from the Cragg estimation using the Cragg estimators are found in Tables 4.21 and 4.22. Results from own-employment time use coefficients are not substantially different from the other estimations.

Some interesting stories emerge from these results. For both males and females, weekday time use is much less responsive to the marginal time use of their partner relative to weekends. This is likely due to individuals being more likely to be in set routines during weekdays with less observed and less possible variability in time use choices. Females do respond to an increase in an hour worked by their partner by participating in about 5 minutes more of their own work according to the OLS regression, although this is not seen in the Cragg regression. This sign of the effect of partner leisure time on female work and leisure time is in opposite directions during weekdays, but they are not precisely estimated. The same sign difference occurs in the result for the male time use. Different signs could occur in the two specifications if the the probability of work is increased as a result of partner leisure time, but the conditional work time falls. An hour of partner household production on weekdays, however, is related with higher female labor supply of 6-9 minutes. Although imprecisely estimated, this may also result in lower household production for females by 3-5 minutes. Marginal male household production seems strongly related to an hour of partner's household production, falling by about 13 minutes during weekdays under both specifications.

On weekends, many of these relationships change. Partner work results in less female work and more female leisure. Partner leisure also generates less female work and quite a bit more female leisure. One hour of partner leisure results in 20 minutes of additional female leisure according to the OLS regression and 15 minutes according to the Cragg regression. The results suggest high complementarity of leisure on weekends, echoing the research in Hamermesh (2002). Additionally, an hour of partner household production is associated with declines in market work for females of 12 minutes, an increase in leisure of 11 minutes and a decrease in household production of 17 minutes when looking at the OLS estimates, although standard errors are somewhat high for each estimate. Although the estimate for leisure is imprecise, the estimate for the effect on own household production is almost a full half hour using the Cragg procedure, suggesting significant substitutability between partner's household production on the weekend, by which the female respondent can increase time in leisure, sleep or other personal activities.

Male work and household production is much more responsive to the time use decisions of their partner relative to those time use categories for females, but their leisure time is much less responsive. An hour of partner work is associated with 11 more minutes of male work during the week and 22 minutes of work on the weekends according the OLS estimates using predicted spousal time use. Incidentally, men spend less time in household production as a result indicating income effects which may work to reduce the time demands on household production. There is some evidence female leisure may even reduce male leisure during the week, and an hour of weekend leisure for females only results in 11 minutes fewer for males, indicating male response to female leisure is much more muted. That said, an hour of household production on the weekend by a partner reduces a male's production by almost the exact same amount as the effect on female. While this paper does not go into detail about the nature of the household production utilized by each gender, a more close analysis of the data could possibly yield the nature of the household production activities that are affected by these seemingly intra-household transfers of responsibility given it appears strong substitutability between the spouses. This, however, could also be an indication of the asynchronicities in the timing of household work, as such an effect does not show up on during the weekday.

4.4 Discussion

In this paper, like past research, I do not find any evidence for a strong added worker effect, but I do calculate a small positive influence for unemployment on spousal labor supply. This measures to be about 1-1.5 hours per week. Controlling for income appears to increase this measurement by a small amount and higher levels of income are associated with higher added worker effects. Increases in household production by spouses due to unemployment do not lead to subsequent large declines in own household production, however each extra hour on household production by the spouse can lead to crowd out one's own production by 15-30 minutes for men all days of the week and for women on weekends.

Although this paper does not model a bargaining process, the empirical evidence found suggests other related insights to the time allocation process for a household. There appear to exist large complementarities to leisure. I do not include wage or income data, but the coefficient estimates for education do not show any noticeable difference between partner's responses to the bargaining power of spouses based on education as found in Connelly and Kimmel (2009b). Additionally, at least on the margin, household production time by a partner does substitute for such time use by the other.

Although we use the same data but different methodologies, my results and those found in Aguiar et al. (2011) find similar measures of the proportion of foregone work hours allocated toward household production. The estimates found in this paper may be slightly larger than theirs, but I include child care in my measure, which they separately distinguish. Regardless, both are important findings because they begin to dispel the notion that unemployment generates substantial "free time" consisting of mostly leisure activity. While this is still partly true, the increase in household production suggests both a shift towards non-market means of household work and possibly a desire to "stay busy." Of course, examining data which focused solely on couples and during a time period of economic instability may contribute to such findings. Gimenez-Nadal et al. (2010) specifically found evidence that unemployed persons are more likely to spend time in household production (versus leisure) when overall unemployment is higher.

Income does not appear to provide substantial variation on the hours changed as a result of respondent's unemployment except for in households making above $100,000. Males see less differences in work time in this income range, indicating they likely spending much more time in job search activities. If unemployment benefits are smaller relative to their household income level, they have a larger incentive to spend time looking for a job. They might also have the resources to not be required to substitute their own time for household production. This effect, however, is unique to male respondents. Female respondents in this income range see higher levels of household production relative to other income groups and no difference in the change in work time. Since income is calculated at the household level, this is likely the result of men being more likely to be the main bread winner in households making over $100,000, but an interesting future research question would be to see if this effect is consistent regardless of the division of the source of household income. While research such as Friedberg and Webb (2006) and Connelly and Kimmel (2009c) has examined the effect of relative household wages, they come to different conclusions regarding whether this generate substantial differences in non-market time use, and neither directly examine the impact of household unemployment.

This research also has implications for unemployment insurance generosity. In addition to findings that they slow job searches, unemployment insurance generosity decreases home production by the recipient (Güler and Taskin, 2013). This is consistent with theory that suggests such insurance payments may be used to purchase market-based substitutes for home production. This also generate significant rethinking of measures of a country's economic well-being. Home production does not contribute to GDP in the same way market-based substitutes would, but to the extent it is utilizing idle resources of the unemployed, it could promote confidence, skill retention and avoidance of malaise that could cloud future job prospects. Additionally, different types of unemployment together to develop a large enough sample, there is theoretical and empirical reasons why different types of unemployment can lead to different types of behavioral adjustment. Dynarski and Sheffrin (1987) notes consumption changes are smaller for those who are laid off and face potential recall than those who are unemployed due to firing, such as with white collar workers and preliminary research by myself suggests such behavior is somewhat reflected in time use data as well. It will be useful to develop this research by better identifying how impacts differ short-term unemployed, long-term unemployed and laid-off workers or how responses differ by the industry or profession. The time use changes of the increasing number of individuals in recent years who have involuntarily moved from full time to part time work can also provide a source of measuring the psychological and economic impact of the labor market changes following the Great Recession.

4.5 Figures and Tables

Table 4.1: **Summary Sample Statistics by Day and Gender : Part 1**

	Female		Male		Full
	Weekday	Weekend	Weekeday	Weekend	Sample
% Black	0.0715	0.0688	0.0749	0.0795	0.0735
	(0.258)	(0.253)	(0.263)	(0.271)	(0.261)
% Hispanic	0.123	0.132	0.118	0.129	0.125
	(0.328)	(0.338)	(0.322)	(0.335)	(0.331)
% Metro area	0.797	0.801	0.799	0.810	0.802
	(0.402)	(0.399)	(0.401)	(0.393)	(0.399)
FT Employment					
Self	0.428	0.439	0.714	0.730	0.570
	(0.495)	(0.496)	(0.452)	(0.444)	(0.495)
Partner	0.681	0.688	0.413	0.420	0.558
	(0.466)	(0.463)	(0.492)	(0.494)	(0.497)
PT Employment					
Self	0.191	0.187	0.0642	0.0580	0.129
	(0.393)	(0.390)	(0.245)	(0.234)	(0.335)
Partner	0.0932	0.0895	0.183	0.187	0.135
	(0.291)	(0.285)	(0.386)	(0.390)	(0.342)
Unemployed					
Self	0.0338	0.0347	0.0323	0.0317	0.0332
	(0.181)	(0.183)	(0.177)	(0.175)	(0.179)
Partner	0.0509	0.0524	0.0653	0.0614	0.0572
	(0.220)	(0.223)	(0.247)	(0.240)	(0.232)
Age					
Age (self)	45.53	45.22	48.33	47.58	46.60
	(14.04)	(14.04)	(14.31)	(14.33)	(14.23)
Age (partner)	47.85	47.47	46.03	45.28	46.71
	(14.40)	(14.39)	(14.07)	(14.03)	(14.27)
N	15758	15963	14246	14250	60217

Sample proportions provided, except for age; sd in parentheses

Table 4.2: **Summary Sample Statistics by Day and Gender : Part 2**

	Female		Male		Full
	Weekday	Weekend	Weekeday	Weekend	Sample
HS degree					
HS Degree (self)	0.910	0.904	0.897	0.892	0.901
	(0.287)	(0.295)	(0.304)	(0.310)	(0.299)
HS D0egree (partner)	0.887	0.880	0.905	0.906	0.894
	(0.316)	(0.325)	(0.293)	(0.291)	(0.308)
BA degree					
Self	0.352	0.350	0.372	0.374	0.361
	(0.478)	(0.477)	(0.483)	(0.484)	(0.480)
Partner	0.358	0.349	0.350	0.357	0.353
	(0.480)	(0.477)	(0.477)	(0.479)	(0.478)
Post-grad degree					
Self	0.119	0.117	0.149	0.149	0.133
	(0.324)	(0.322)	(0.356)	(0.356)	(0.339)
Partner	0.139	0.137	0.116	0.123	0.129
	(0.346)	(0.344)	(0.321)	(0.328)	(0.335)
Male Partner	0.996	0.995	0.00358	0.00484	0.526
	(0.0656)	(0.0679)	(0.0597)	(0.0694)	(0.499)
Any HH Child	0.596	0.597	0.572	0.596	0.590
	(0.491)	(0.491)	(0.495)	(0.491)	(0.492)
Child 5 or under	0.291	0.299	0.281	0.294	0.292
	(0.454)	(0.458)	(0.449)	(0.456)	(0.455)
Child 10 or under	0.447	0.451	0.425	0.448	0.443
	(0.497)	(0.498)	(0.494)	(0.497)	(0.497)
N	15758	15963	14246	14250	60217

Sample proportions provided, except for age; sd in parentheses

Table 4.3: **Summary Sample Statistics by Income : Part 1**

	$0- $30,000	$30,000- $50,000	$50,000- $75,000	$75,000- $100,000	$over $100,000	Full Sample
% Black	0.116	0.0835	0.0646	0.0531	0.0416	0.0735
	(0.320)	(0.277)	(0.246)	(0.224)	(0.200)	(0.261)
% Hispanic	0.285	0.170	0.0911	0.0619	0.0542	0.125
	(0.452)	(0.376)	(0.288)	(0.241)	(0.226)	(0.331)
% Metro area	0.715	0.739	0.788	0.864	0.915	0.802
	(0.451)	(0.439)	(0.408)	(0.343)	(0.279)	(0.399)
FT Employment						
Self	0.349	0.502	0.628	0.686	0.703	0.570
	(0.477)	(0.500)	(0.483)	(0.464)	(0.457)	(0.495)
Partner	0.334	0.503	0.615	0.670	0.692	0.558
	(0.472)	(0.500)	(0.487)	(0.470)	(0.462)	(0.497)
PT Employment						
Self	0.129	0.135	0.132	0.127	0.123	0.129
	(0.335)	(0.342)	(0.338)	(0.333)	(0.329)	(0.335)
Partner	0.139	0.137	0.139	0.134	0.130	0.135
	(0.346)	(0.344)	(0.346)	(0.341)	(0.337)	(0.342)
Unemployed						
Self	0.0596	0.0402	0.0311	0.0225	0.0171	0.0332
	(0.237)	(0.197)	(0.174)	(0.148)	(0.130)	(0.179)
Partner	0.0848	0.0636	0.0525	0.0453	0.0422	0.0572
	(0.279)	(0.244)	(0.223)	(0.208)	(0.201)	(0.232)
Age						
Self	47.74	46.56	45.12	44.94	45.91	46.60
	(18.01)	(15.76)	(13.19)	(11.39)	(10.53)	(14.23)
Partner	47.98	46.79	45.22	45.01	45.89	46.71
	(18.12)	(15.81)	(13.22)	(11.39)	(10.49)	(14.27)
N	9408	10763	12277	10599	10138	60217

Sample proportions provided, except for age and time use; standard deviations in parentheses

Table 4.4: **Summary Sample Statistics by Income : Part 2**

	\$0- \$30,000	\$30,000- \$50,000	\$50,000- \$75,000	\$75,000- \$100,000	\$over \$100,000	Full Sample
HS degree						
Self	0.690	0.870	0.954	0.983	0.991	0.901
	(0.463)	(0.336)	(0.209)	(0.130)	(0.0933)	(0.299)
Partner	0.677	0.860	0.947	0.982	0.989	0.894
	(0.468)	(0.347)	(0.224)	(0.131)	(0.106)	(0.308)
BA degree						
Self	0.0933	0.183	0.334	0.529	0.695	0.361
	(0.291)	(0.386)	(0.472)	(0.499)	(0.461)	(0.480)
Partner	0.0940	0.172	0.325	0.521	0.685	0.353
	(0.292)	(0.378)	(0.468)	(0.500)	(0.465)	(0.478)
Post-grad degree						
Self	0.0223	0.0484	0.0968	0.198	0.316	0.133
	(0.148)	(0.215)	(0.296)	(0.398)	(0.465)	(0.339)
Partner	0.0232	0.0437	0.0934	0.196	0.307	0.129
	(0.150)	(0.204)	(0.291)	(0.397)	(0.461)	(0.335)
Any HH Child	0.527	0.558	0.615	0.641	0.677	0.590
	(0.499)	(0.497)	(0.487)	(0.480)	(0.468)	(0.492)
Child 5 or under	0.316	0.298	0.308	0.295	0.292	0.292
	(0.465)	(0.457)	(0.462)	(0.456)	(0.455)	(0.455)
Child 10 or under	0.430	0.433	0.465	0.467	0.486	0.443
	(0.495)	(0.496)	(0.499)	(0.499)	(0.500)	(0.497)
N	9408	10763	12277	10599	10138	60217

Sample proportions provided, except for age and time use; standard deviations in parentheses

Table 4.5: **Mean Average Times and Participation Rates for Weekdays** (min/day)

	Full Sample	Females	Males	\$0- \$30,000	\$30,000- \$50,000	\$50,000- \$75,000	\$75,000- \$100,000	above \$100,000
Work	284.1	220.7	354.3	175.8	250.4	309.5	338.4	356.7
	(267.9)	(247.6)	(272.0)	(245.2)	(266.6)	(263.2)	(262.2)	(261.7)
Leis	248.1	235.4	262.1	310.4	271.9	235.2	211.1	202.1
	(185.1)	(170.2)	(199.4)	(213.1)	(195.5)	(173.4)	(157.8)	(151.9)
HHPr	212.0	276.4	140.9	233.0	218.5	208.2	203.7	196.9
	(190.9)	(199.0)	(152.8)	(201.0)	(194.0)	(186.1)	(186.5)	(184.4)
Pr(Work)	0.604	0.512	0.705	0.396	0.539	0.656	0.710	0.739
	(0.489)	(0.500)	(0.456)	(0.489)	(0.499)	(0.475)	(0.454)	(0.439)
Pr(Leis)	0.958	0.959	0.957	0.964	0.960	0.962	0.954	0.953
	(0.200)	(0.197)	(0.202)	(0.187)	(0.197)	(0.191)	(0.210)	(0.211)
Pr(HHPr)	0.919	0.972	0.860	0.907	0.914	0.925	0.927	0.925
	(0.273)	(0.165)	(0.347)	(0.290)	(0.281)	(0.264)	(0.261)	(0.263)
N	30004	15758	14246	4688	5305	6151	5241	4982

Standard deviations in parentheses

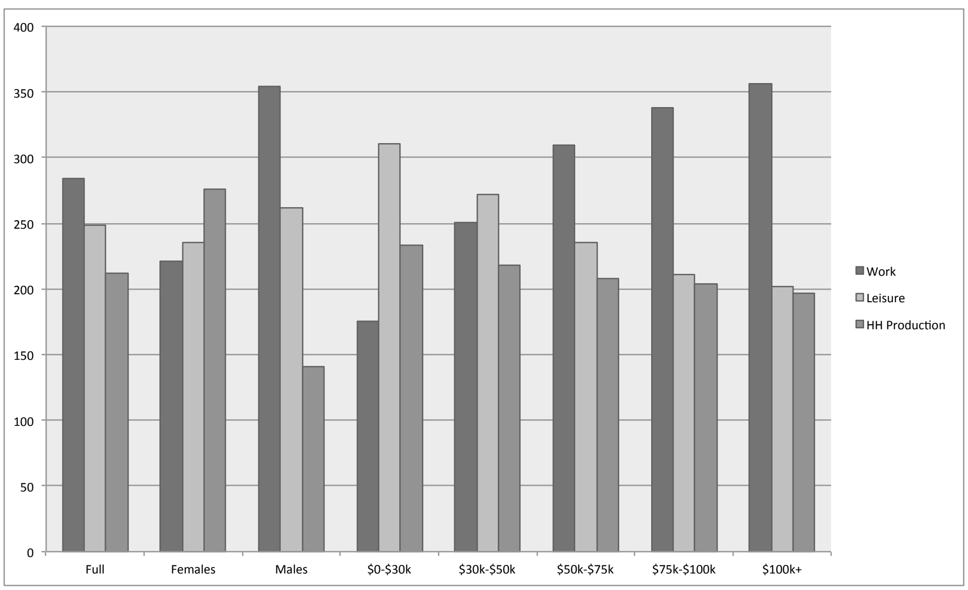


Table 4.6: **Mean Average Times and Participation Rates for Weekends** (min/day)

	Full Sample	Females	Males	\$0-\$30,000	\$30,000-\$50,000	\$50,000-\$75,000	\$75,000-\$100,000	above \$100,000
Work	71.79	51.04	95.04	68.90	74.20	76.51	72.35	67.04
	(173.0)	(143.1)	(198.7)	(173.2)	(180.0)	(178.5)	(171.1)	(159.7)
Leis	363.3	333.5	396.7	398.3	375.6	358.7	341.5	333.0
	(203.3)	(186.5)	(215.7)	(221.2)	(208.2)	(200.6)	(190.2)	(185.4)
HHPr	248.5	288.6	203.4	213.6	235.4	251.8	270.3	277.1
	(190.9)	(188.6)	(183.1)	(191.7)	(189.4)	(190.4)	(189.8)	(185.2)
Pr(Work)	0.245	0.194	0.302	0.183	0.209	0.254	0.273	0.311
	(0.430)	(0.395)	(0.459)	(0.387)	(0.407)	(0.435)	(0.446)	(0.463)
Pr(Leis)	0.976	0.977	0.975	0.976	0.978	0.976	0.974	0.977
	(0.153)	(0.151)	(0.156)	(0.154)	(0.148)	(0.155)	(0.158)	(0.151)
Pr(HHPr)	0.921	0.963	0.874	0.876	0.918	0.928	0.943	0.948
	(0.270)	(0.189)	(0.332)	(0.330)	(0.274)	(0.259)	(0.232)	(0.222)
N	30213	15963	14250	4720	5458	6126	5358	5156

Standard deviations in parentheses

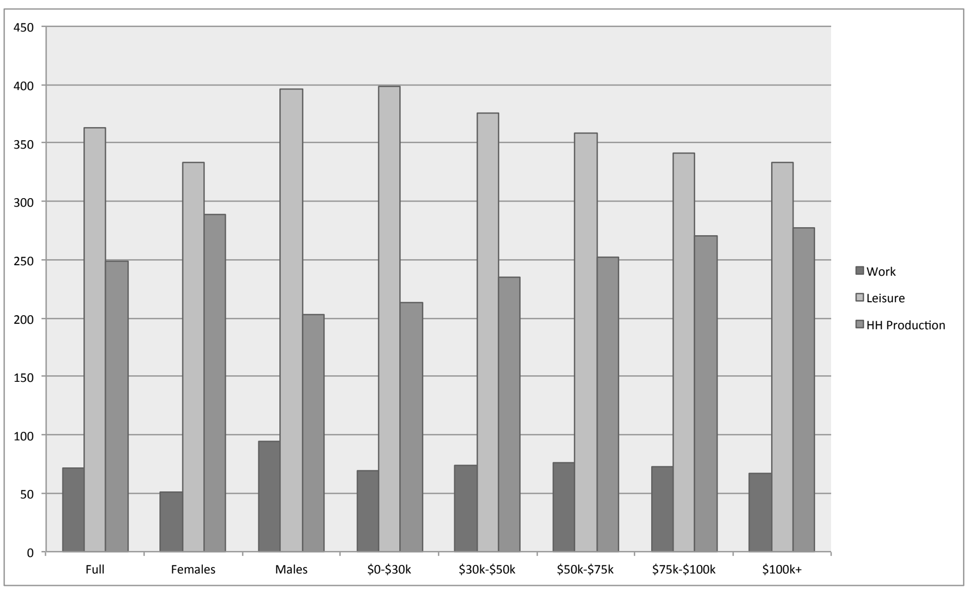


Table 4.7: **Time Use Effects of Full Employment to Unemployment**
(Hours per week change in each activity)

	Work		Leisure		HH Production	
	OLS	CRAGG	OLS	CRAGG	OLS	CRAGG
FEMALE						
Self	-34.67	-32.70	12.23	12.35	17.69	21.13
	(0.35)	(1.09)	(0.35)	(0.33)	(0.38)	(0.36)
Partner	1.37	1.50	0.51	0.51	-2.23	-2.05
	(0.36)	(0.36)	(0.36)	(0.39)	(0.39)	(0.46)
MALE						
Self	-36.36	-38.27	14.56	13.49	16.14	12.70
	(0.52)	(1.84)	(0.47)	(0.48)	(0.41)	(0.38)
Partner	0.80	1.13	0.14	0.19	-2.44	-2.28
	(0.36)	(0.37)	(0.33)	(0.33)	(0.29)	(0.30)

Estimates constructed from 5 times the weekday coefficients plus twice the weekend coefficients divided by 60 to convert to hours. Bootstrapped standard errors report for Cragg estimates.

Table 4.8: **Time Use Effects of Full Employment to Unemployment with income controls**

(Hours per week change in each activity)

	Work		Leisure		HH Production	
	OLS	CRAGG	OLS	CRAGG	OLS	CRAGG
FEMALE						
Self	-34.41	-32.51	11.65	11.80	17.64	20.86
	(0.37)	(1.12)	(0.37)	(0.32)	(0.40)	(0.41)
Partner	1.53	1.74	0.13	0.12	-2.17	1.98
	(0.40)	(0.42)	(0.39)	(0.40)	(0.42)	(0.47)
MALE						
Self	-36.07	-38.80	14.41	13.51	15.93	12.53
	(0.56)	(2.21)	(0.50)	(0.48)	(0.44)	(0.41)
Partner	1.27	1.59	-0.01	0.03	-2.34	-2.22
	(0.39)	(0.38)	(0.35)	(0.38)	(0.31)	(0.35)

Estimates constructed from 5 times the weekday coefficients plus twice the weekend coefficients divided by 60 to convert to hours. Bootstrapped standard errors report for Cragg estimates.

Table 4.9: **OLS Estimates of the Effect of Employment Status on Time Use for Females**

(Minutes per day change in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment (self)	403.2***	-131.5***	-215.4***	82.86***	-55.30***	-18.70***
	(3.373)	(3.050)	(3.409)	(2.852)	(3.635)	(3.695)
FT employment (partner)	2.278	-19.28***	35.20***	-0.202	-24.22***	25.61***
	(4.871)	(4.404)	(4.924)	(4.182)	(5.330)	(5.418)
PT employment (self)	202.0***	-72.89***	-106.9***	70.49***	-36.39***	-30.08***
	(3.923)	(3.547)	(3.966)	(3.335)	(4.250)	(4.320)
PT employment (partner)	12.18*	-27.54***	28.20***	10.20*	-15.90*	5.857
	(5.849)	(5.289)	(5.912)	(5.033)	(6.415)	(6.520)
Unemployed	18.44*	-2.853	-14.24	4.677	-10.08	9.059
	(7.555)	(6.831)	(7.637)	(6.271)	(7.993)	(8.125)
Unemployed (partner)	11.41	-16.66**	18.46*	18.09**	-15.43*	0.522
	(7.104)	(6.423)	(7.181)	(5.952)	(7.586)	(7.711)
Male partner	-71.71***	1.009	62.44**	-32.75*	15.68	26.46
	(19.92)	(18.01)	(20.13)	(16.13)	(20.56)	(20.90)
Age (Self)	1.885	-2.743**	7.350***	-1.384	-3.253**	7.500***
	(1.131)	(1.023)	(1.143)	(0.947)	(1.207)	(1.227)
Age (Partner)	-1.079	-0.385	0.344	0.339	-1.898	2.332
	(1.139)	(1.030)	(1.152)	(0.959)	(1.223)	(1.243)
Age^2 (Self)	-0.0265*	0.0428***	-0.0733***	0.00994	0.0472***	-0.0749***
	(0.0114)	(0.0103)	(0.0115)	(0.00960)	(0.0122)	(0.0124)
Age^2 (Partner)	0.0126	-0.00124	0.000539	-0.00155	0.0101	-0.0150
	(0.0112)	(0.0101)	(0.0113)	(0.00943)	(0.0120)	(0.0122)
Any HH Child	-7.021	-18.77***	45.42***	1.234	-24.75***	32.93***
	(4.310)	(3.897)	(4.356)	(3.654)	(4.657)	(4.733)
Child under 5	-15.29***	-28.86***	64.61***	1.722	-39.20***	63.50***
	(4.305)	(3.892)	(4.351)	(3.633)	(4.631)	(4.707)
Child under 10	-6.291	-20.69***	36.05***	-5.366	-18.78***	36.50***
	(4.792)	(4.333)	(4.844)	(4.077)	(5.196)	(5.282)
Observations	15758	15758	15758	15963	15963	15963

Unreported regressors include education, black and hispanic indicators for both partners, as well as controls for day of week, month, year and state.

Standard errors in parentheses

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

Table 4.10: **OLS Estimates of the Effect of Employment Status on Time Use for Females with Income Indicators**

(Minutes per day change in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment	401.3***	-129.3***	-215.4***	84.53***	-53.17***	-21.72***
	(3.643)	(3.274)	(3.634)	(3.068)	(3.897)	(3.952)
FT employment (partner)	-2.371	-18.12***	37.18***	2.899	-20.86***	22.52***
	(5.387)	(4.840)	(5.373)	(4.598)	(5.840)	(5.924)
PT employment	201.2***	-71.01***	-106.4***	71.25***	-34.07***	-31.96***
	(4.189)	(3.764)	(4.178)	(3.553)	(4.512)	(4.577)
PT employment (partner)	9.857	-27.77***	30.72***	11.31*	-12.70	5.846
	(6.357)	(5.712)	(6.341)	(5.452)	(6.925)	(7.024)
Unemployed	21.33**	-6.746	-16.59*	2.381	-10.01	10.12
	(8.119)	(7.296)	(8.098)	(6.598)	(8.381)	(8.501)
Unemployed (partner)	8.448	-18.64**	20.89**	22.14***	-15.72	-1.966
	(7.702)	(6.920)	(7.681)	(6.370)	(8.092)	(8.207)
Male Partner	-64.90**	2.883	60.89**	-32.49	32.36	13.06
	(21.08)	(18.94)	(21.03)	(17.00)	(21.60)	(21.91)
Age	1.661	-2.609*	7.318***	-0.949	-3.653**	7.563***
	(1.224)	(1.100)	(1.221)	(1.017)	(1.292)	(1.311)
Age (partner)	-1.702	0.642	0.425	0.459	-1.168	1.700
	(1.225)	(1.101)	(1.222)	(1.027)	(1.304)	(1.323)
Age^2	-0.0247*	0.0418***	-0.0721***	0.00593	0.0533***	-0.0764***
	(0.0124)	(0.0111)	(0.0124)	(0.0104)	(0.0132)	(0.0134)
Age^2 (partner)	0.0186	-0.0122	-0.000184	-0.00274	0.00116	-0.00820
	(0.0121)	(0.0108)	(0.0120)	(0.0102)	(0.0129)	(0.0131)
Any HH Child	-5.600	-20.29***	46.60***	1.813	-24.32***	32.74***
	(4.624)	(4.155)	(4.612)	(3.886)	(4.936)	(5.007)
Child under 5	-14.83**	-30.19***	65.34***	1.309	-41.22***	64.72***
	(4.544)	(4.083)	(4.532)	(3.821)	(4.853)	(4.922)
Child under 10	-9.422	-20.40***	38.44***	-3.391	-18.95***	36.24***
	(5.098)	(4.581)	(5.085)	(4.310)	(5.475)	(5.553)
HH Income \$30k-\$50k	4.259	-4.489	-1.473	-5.417	-4.444	3.809
	(4.748)	(4.266)	(4.736)	(3.922)	(4.982)	(5.054)
HH Income \$50k-\$75k	16.59***	-7.604	-9.873*	-16.56***	-5.763	14.00**
	(4.969)	(4.465)	(4.956)	(4.147)	(5.267)	(5.342)
HH Income \$75k-\$100k	14.48**	-15.70**	-5.485	-23.79***	-11.61*	23.20***
	(5.487)	(4.931)	(5.473)	(4.560)	(5.792)	(5.875)
HH Income \$100k+	28.44***	-19.33***	-13.54*	-20.53***	-16.16*	28.92***
	(6.013)	(5.403)	(5.997)	(4.965)	(6.307)	(6.397)
Observations	13841	13841	13841	14177	14177	14177

Standard errors in parentheses

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

Table 4.11: **OLS Estimates of the Effect of Employment Status on Time Use for Males**
(Minutes per day change in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment (self)	443.4***	-230.8***	-135.4***	123.5***	-120.6***	7.569
	(5.678)	(4.752)	(4.223)	(5.723)	(6.033)	(5.238)
FT employment (partner)	-11.66**	-5.272	25.89***	-2.799	-8.999*	19.33***
	(4.259)	(3.564)	(3.168)	(4.241)	(4.470)	(3.881)
PT employment (self)	237.2***	-150.4***	-70.58***	96.96***	-92.66***	4.268
	(7.711)	(6.454)	(5.735)	(8.008)	(8.440)	(7.328)
PT employment (partner)	-6.115	-1.392	14.18***	-0.00690	-10.91*	13.44**
	(4.973)	(4.162)	(3.699)	(4.951)	(5.219)	(4.531)
Unemployed	51.25***	-83.19***	39.98***	13.15	-52.78***	53.21***
	(10.30)	(8.617)	(7.658)	(10.42)	(10.98)	(9.533)
Unemployed (Partner)	-4.651	-6.110	2.112	3.641	-2.682	5.687
	(7.048)	(5.898)	(5.242)	(7.230)	(7.621)	(6.616)
Male Partner	-38.42	12.81	3.592	9.757	-30.38	17.63
	(27.09)	(22.68)	(20.15)	(23.31)	(24.57)	(21.33)
Age (Self)	-0.109	-2.386*	3.966***	1.343	-3.602*	6.195***
	(1.384)	(1.158)	(1.029)	(1.364)	(1.437)	(1.248)
Age (Partner)	2.676*	0.990	-0.658	-2.023	0.522	1.083
	(1.353)	(1.133)	(1.006)	(1.341)	(1.414)	(1.227)
Age^2	-0.00717	0.0304**	-0.0403***	-0.00661	0.0337*	-0.0621***
	(0.0136)	(0.0114)	(0.0101)	(0.0134)	(0.0142)	(0.0123)
Age^2 (Partner)	-0.0265	-0.00934	0.0127	0.0114	0.00220	-0.00655
	(0.0137)	(0.0114)	(0.0102)	(0.0136)	(0.0143)	(0.0124)
Any HH Child	2.092	-15.97***	10.59**	2.833	-4.613	10.47*
	(5.317)	(4.450)	(3.954)	(5.327)	(5.615)	(4.875)
Child under 5	-2.295	-11.33*	32.59***	-4.447	-22.02***	43.40***
	(5.471)	(4.579)	(4.069)	(5.330)	(5.617)	(4.877)
Child under 10	-6.438	-14.57**	29.30***	-12.32*	-23.78***	34.37***
	(6.047)	(5.061)	(4.497)	(5.941)	(6.261)	(5.436)
Observations	14246	14246	14246	14250	14250	14250

Unreported regressors include education, black and hispanic indicators for both partners, as well as controls for day of week, month, year and state.

Standard errors in parentheses

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

Table 4.12: **OLS Estimates of the Effect of Employment Status on Time Use for Males with Income Indicators**

(Minutes per day change in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment	440.1***	-228.5***	-134.5***	126.3***	-119.3***	3.626
	(6.332)	(5.226)	(4.643)	(6.305)	(6.633)	(5.764)
FT employment (partner)	-15.24**	-3.427	24.74***	1.777	-9.202	14.22***
	(4.662)	(3.848)	(3.419)	(4.576)	(4.814)	(4.183)
PT employment	243.0***	-154.2***	-70.75***	99.48***	-92.58***	4.434
	(8.469)	(6.990)	(6.211)	(8.532)	(8.976)	(7.800)
PT employment (partner)	-7.879	-0.780	15.17***	3.766	-11.99*	10.01*
	(5.359)	(4.424)	(3.930)	(5.273)	(5.548)	(4.821)
Unemployed	52.02***	-80.45***	35.66***	14.51	-56.87***	55.96***
	(11.01)	(9.089)	(8.076)	(11.12)	(11.70)	(10.17)
Unemployed (partner)	-1.032	-5.779	-0.445	4.303	-3.472	7.038
	(7.588)	(6.263)	(5.565)	(7.712)	(8.113)	(7.050)
Male Partner	-39.50	10.81	4.093	14.83	-40.90	23.35
	(27.71)	(22.87)	(20.32)	(24.06)	(25.32)	(22.00)
Age	-0.720	-1.929	3.945***	1.596	-3.551*	5.793***
	(1.493)	(1.233)	(1.095)	(1.471)	(1.548)	(1.345)
Age (partner)	2.634	1.302	-1.263	-1.035	0.237	0.828
	(1.471)	(1.214)	(1.079)	(1.445)	(1.520)	(1.321)
Age^2	-0.00236	0.0264*	-0.0398***	-0.00909	0.0325*	-0.0573***
	(0.0149)	(0.0123)	(0.0109)	(0.0146)	(0.0154)	(0.0134)
Age^2 (partner)	-0.0260	-0.0125	0.0187	0.00258	0.00612	-0.00620
	(0.0151)	(0.0124)	(0.0111)	(0.0147)	(0.0155)	(0.0135)
Any HH Child	-1.270	-13.83**	11.01**	1.383	-2.090	9.752
	(5.729)	(4.729)	(4.201)	(5.680)	(5.975)	(5.192)
Child under 5	-1.451	-11.55*	32.01***	-3.086	-24.19***	43.01***
	(5.815)	(4.800)	(4.264)	(5.598)	(5.889)	(5.117)
Child under 10	-5.611	-16.37**	29.44***	-10.87	-24.14***	35.23***
	(6.452)	(5.325)	(4.731)	(6.280)	(6.607)	(5.741)
HH Income \$30k-\$50k	5.401	-1.637	9.632*	-11.22	-1.328	16.60**
	(5.898)	(4.868)	(4.325)	(5.867)	(6.172)	(5.363)
HH Income \$50k-\$75k	8.586	-8.360	15.33***	-16.12**	1.220	19.70***
	(6.203)	(5.120)	(4.549)	(6.130)	(6.449)	(5.604)
HH Income \$75k-\$100k	20.03**	-15.59**	10.54*	-22.51***	-4.811	32.49***
	(6.816)	(5.626)	(4.998)	(6.730)	(7.080)	(6.152)
HH Income \$100k+	25.86***	-10.88	7.446	-37.17***	-3.875	34.34***
	(7.390)	(6.100)	(5.419)	(7.325)	(7.706)	(6.696)
Observations	12526	12526	12526	12641	12641	12641

Standard errors in parentheses

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

Table 4.13: **Cragg Estimates of the Effect of Employment Status on Time Use for Females**

(Minutes per day change in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment	385.3***	-131.3***	-207.7***	126.5***	-55.43***	-17.90 ***
	(15.9)	(2.83)	(3.54)	(6.82)	(4.07)	(3.348)
FT employment (partner)	4.477	-13.81**	31.67***	3.123	-22.52***	25.84***
	(5.000)	(4.507)	(5.474)	(4.340)	(5.595)	(5.950)
PT employment	258.9***	-64.51***	-86.25***	116.8***	-35.74***	-28.93 ***
	(17.64)	(3.26)	(3.50)	(7.53)	(4.52)	(4.12)
PT employment (partner)	16.04*	-20.62***	24.44***	13.72*	-13.70*	6.472
	(6.46)	(5.11)	(6.55)	(5.94)	(6.07)	(6.61)
Unemployed	38.81	-1.324	34.50***	11.86	-9.704	10.33
	(21.79)	(5.976)	(6.97)	(16.62)	(8.18)	(8.27)
Unemployed (partner)	16.74*	-11.21	16.12	17.34**	-13.72	3.252
	(6.96)	(7.135)	(8.57)	(5.76)	(8.156)	(9.495)
Male Partner	-57.58**	-1.550	109.6***	-22.99	17.00	30.68
	(20.61)	(23.416)	(26.107)	(13.385)	(30.90)	(37.95)
Age	4.442**	-1.647	6.485***	-0.951	-2.883**	8.192***
	(1.303)	(1.109	(1.139)	(0.946)	(1.048)	(1.311)
Age (partner)	-1.404	-0.400	0.578	0.655	-2.033	2.069
	(1.186)	(1.119)	(1.146)	(1.016)	(1.197)	(1.403)
Age^2	-0.0574***	0.0275**	-0.0590***	0.00589	0.0422**	-0.0830***
	(.01225)	(0.00865)	(0.01296)	(0.01169)	(0.01217)	(0.01225)
Age^2 (partner)	0.0168	-0.00107	-0.000994	-0.00442	0.0112	-0.0120
	(0.01188)	(0.00914)	(0.01156)	(0.01086)	(0.01300)	(0.01408)
Any HH Child	-8.459*	-19.22***	55.89***	-0.445	-24.21***	34.76***
	(3.820)	(3.640)	(4.785)	(3.967)	(4.377)	(4.476)
Child under 5	-13.48**	-31.43***	59.33***	2.486	-41.51***	59.86***
	(3.874)	(3.416)	(3.727)	(3.553)	(4.666)	(4.250)
Child under 10	-5.906	-23.50***	39.68 ***	-3.110	-19.54***	35.73***
	(4.300)	(4.858)	(4.555)	(4.089)	(5.303)	(5.113)
N	15758	15758	15758	15963	15963	15963

Unreported regressors include education, black and hispanic indicators for both partners, as well as controls for day of week, month, year and state.

Bootstrapped standard errors reported.

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

Table 4.14: **Cragg Estimates of the Effect of Employment Status on Time Use for Females with income controls**

(Minutes per day change in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment	386.8***	-128.6***	-206.8***	124.8***	-53.34***	-20.95***
	(16.10)	(3.74)	(3.13)	(8.65)	(3.46)	(3.86)
FT employment (partner)	-0.642	-12.21**	33.50***	7.158	-19.35**	22.42***
	(5.64)	(5.33)	(4.52)	(4.70)	(6.91)	(6.75)
PT employment	259.8***	-62.55***	-84.87***	114.2***	-33.39***	-30.82***
	(18.11)	(3.31)	(3.55)	(6.67)	(3.83)	(4.47)
PT employment (partner)	12.93	-20.37***	26.76**	15.78*	-10.72	6.425
	(7.28)	(5.85)	(8.72)	(6.21)	(6.15)	(8.42)
Unemployed	46.88	-4.618	30.69***	-0.703	-9.178	11.02
	(21.43)	(5.50)	(8.56)	(19.44)	(7.62)	(9.33)
Unemployed (partner)	14.29	-12.88	18.45*	21.90***	-14.12*	0.581
	(8.60)	(6.79)	(9.25)	(5.47)	(7.00)	(9.64)
Male Partner	-52.81**	-0.238	105.2***	-23.67	33.77	14.57
	(19.48)	(16.57)	(25.13)	(13.30)	(38.43)	(28.36)
Age	4.100***	-1.528**	6.407***	-0.151	-3.205*	8.294***
	(1.1805)	(0.9943)	(1.1052)	(1.0679)	(1.3247)	(1.3431)
Age (partner)	-2.130	0.431	0.683	0.557	-1.376	1.411
	(1.1228)	(0.9945)	(1.3398)	(1.1004)	(1.2724)	(1.5140)
Age^2	-0.0544***	0.0265	-0.0568***	-0.00344	0.0473***	-0.0849***
	(0.0141)	(0.0099)	(0.0131)	(0.0124)	(0.0133)	(0.0149)
Age^2 (partner)	0.0242	-0.00973	-0.00216	-0.00274	0.00314	-0.00491
	(0.0139)	(0.0115)	(0.0151)	(0.0106)	(0.0114)	(0.0131)
Any HH Child	-6.961	-19.99***	57.65***	-0.0691	-23.59***	34.87***
	(3.94)	(4.84)	(5.06)	(3.21)	(4.98)	(6.03)
Child under 5	-14.27***	-33.63***	59.71***	2.119	-43.65***	61.17***
	(4.23)	(3.66)	(4.49)	(3.91)	(4.56)	(5.54)
Child under 10	-8.362	-22.88***	42.72***	-1.789	-19.74***	35.84***
	(4.45)	(4.39)	(4.80)	(4.05)	(4.66)	(4.51)
HH Income \$30k-\$50k	7.163	-3.150	-2.737	-5.659	-4.021	3.884
	(5.69)	(3.97)	(5.30)	(3.47)	(5.43)	(4.49)
HH Income \$50k-\$75k	18.33***	-5.265	-11.17*	-15.52***	-5.195	14.46**
	(4.60)	(4.86)	(4.90)	(3.42)	(5.41)	(5.24)
HH Income \$75k-\$100k	15.93***	-14.78***	-6.042	-22.49***	-11.26	23.78***
	(5.39)	(4.55)	(4.57)	(4.32)	(6.28)	(5.17)
HH Income \$100k+	27.01***	-19.86***	-13.36*	-18.71***	-16.07**	29.26***
	(6.32)	(4.74)	(6.33)	(4.64)	(5.68)	(6.39)
N	13841	13841	13841	14177	14177	14177

Unreported regressors include education, black and hispanic indicators for both partners, as well as controls for day of week, month, year and state.

Bootstrapped standard errors reported.

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

Table 4.15: **Cragg Estimates of the Effect of Employment Status on Time Use for Males**
(Minutes per day change in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment	450.7***	-184.1***	-119.0***	219.2***	-114.0***	8.857
	(26.45)	(4.40)	(4.23)	(27.29)	(5.51)	(5.695)
FT employment (partner)	-9.539*	-3.791	23.38***	-3.760	-8.653	19.15
	(4.256)	(3.442)	(3.08)	(3.73)	(4.56)	(3.87)
PT employment	288.5***	-102.9***	-52.78***	196.7***	-85.31***	6.500
	(28.27)	(6.48)	(5.34)	(22.70)	(9.635)	(7.47)
PT employment (partner)	-4.366	-0.429	13.16***	0.519	-10.75*	13.45
	(5.183)	(3.928)	(3.734)	(4.435)	(5.150)	(4.672)
Unemployed	62.21*	-49.76***	16.28**	42.12	-45.19**	51.75
	(30.96)	(7.19)	(5.70)	(34.23)	(14.222)	(10.03)
Unemployed (partner)	0.772	-3.965	0.760	4.423	-2.480	7.266
	(7.435)	(6.077)	(5.603)	(7.335)	(7.180)	(6.665)
Male Partner	-34.91	12.13	1.420	16.43	-29.97	19.71
	(31.51)	(33.37)	(21.62)	(27.61)	(33.68)	(18.63)
Age	2.379	-1.704	3.005	1.323*	-3.504*	6.987
	(1.614)	(1.234)	(1.223)	(1.479)	(1.513)	(1.501)
Age (partner)	3.672*	0.719	0.0322	-1.017	0.552	1.169
	(1.584)	(1.129)	(0.870)	(1.381)	(1.441)	(1.386)
Age^2	-0.0360*	0.0229*	-0.0296*	-0.00716	0.0319*	-0.0713
	(0.016)	(0.011)	(0.0117)	(0.0147)	(0.0138)	(0.0139)
Age^2 (partner)	-0.0398*	-0.00738	0.00687	0.00113	0.00193	-0.00795
	(0.0163)	(0.0095)	(0.00894)	(0.01692)	(0.0133)	(0.0167)
Any HH Child	-2.278	-15.09**	11.83*	1.036	-4.286	11.96
	(5.405)	(4.464)	(4.461)	(4.908)	(5.762)	(5.273)
Child under 5	-1.389	-13.54*	32.42***	-3.797	-23.07***	40.06
	(4.224)	(5.283)	(4.387)	(5.392)	(6.260)	(4.370)
Child under 10	-7.260	-18.60**	33.63***	-9.680	-24.80***	32.68
	(6.526)	(5.389)	(4.346)	(6.080)	(7.082)	(4.997)
N	14246	14246	14246	14250	14250	14250

Unreported regressors include education, black and hispanic indicators for both partners, as well as controls for day of week, month, year and state.
Bootstrapped standard errors reported.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.16: **Cragg Estimates of the Effect of Employment Status on Time Use for Males with income controls**

(Minutes per day change in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment	458.5***	-180.6***	-116.8***	218.7***	-112.4***	5.747
	(29.10)	(5.04)	(3.46)	(23.31)	(5.94)	(7.10)
FT employment (partner)	-12.69**	-1.883	22.02***	0.833	-8.933	14.20***
	(4.91)	(4.00)	(3.59)	(3.81)	(5.18)	(3.81)
PT employment	301.1***	-105.5***	-52.54***	195.4***	-84.96***	7.403
	(34.41)	(7.09)	(6.18)	(25.97)	(10.44)	(8.77)
PT employment (partner)	-5.716	0.294	14.24***	4.070	-11.83	9.878*
	(5.83)	(4.65)	(3.80)	(4.56)	(6.21)	(4.04)
Unemployed	63.40	-48.00***	13.75*	42.51	-49.50***	55.40***
	(44.05)	(7.31)	(6.73)	(35.79)	(13.26)	(10.38)
Unemployed (partner)	4.266	-3.810	-2.416	6.013	-3.332	8.583
	(7.63)	(6.14)	(6.00)	(5.80)	(9.76)	(8.83)
Male Partner	-36.65	11.14	1.436	22.15	-40.77	25.65
	(29.10)	(44.93)	(21.54)	(23.70)	(33.54)	(18.93)
Age	2.230	-1.352	3.045	1.356	-3.436	6.442***
	(1.4500)	(1.2540)	(1.1841)	(1.6855)	(1.8491)	(1.4657)
Age (partner)	3.315*	1.047	-0.560	0.383	0.232	1.107
	(1.4832)	(1.0826)	(1.1492)	(1.3107)	(1.6891)	(1.4606)
Age^2	-0.0370**	0.0201	-0.0295**	-0.00670	0.0305*	-0.0648***
	(0.0141)	(0.0105)	(0.0113)	(0.0172)	(0.0151)	(0.0141)
Age^2 (partner)	-0.0351	-0.0109	0.0125	-0.0132	0.00623	-0.00983
	(0.0182)	(0.0112)	(0.0108)	(0.0176)	(0.0166)	(0.0147)
Any HH Child	-4.896	-12.43**	12.35***	-0.572	-1.764	11.36
	(5.72)	(4.77)	(3.74)	(5.83)	(5.95)	(5.93)
Child under 5	-1.094	-14.32*	31.69***	-3.153	-25.24	39.82***
	(6.49)	(6.06)	(4.50)	(5.83)	(6.51)	(4.30)
Child under 10	-6.443	-20.21***	33.70	-8.082	-25.11***	33.78***
	(5.02)	(5.76)	(5.34)	(5.45)	(6.64)	(5.68)
HH Income \$30k-\$50k	5.525	0.0230***	7.287	-13.63*	-0.575	18.31***
	(6.81)	(4.89)	(4.35)	(5.68)	(5.73)	(5.64)
HH Income \$50k-\$75k	8.386**	-6.594	12.93	-17.82**	1.926	21.31***
	(5.94)	(4.80)	(4.88)	(6.35)	(4.97)	(5.94)
HH Income \$75k-\$100k	18.50***	-14.94*	9.173	-24.60***	-4.172	32.90***
	(5.79)	(6.74)	(4.73)	(6.03)	(6.30)	(6.61)
HH Income \$100k+	24.82**	-10.20	5.332	-39.60***	-3.228	34.89***
	(8.09)	(6.59)	(5.54)	(8.31)	(7.28)	(6.96)
N	12526	12526	12526	12641	12641	12641

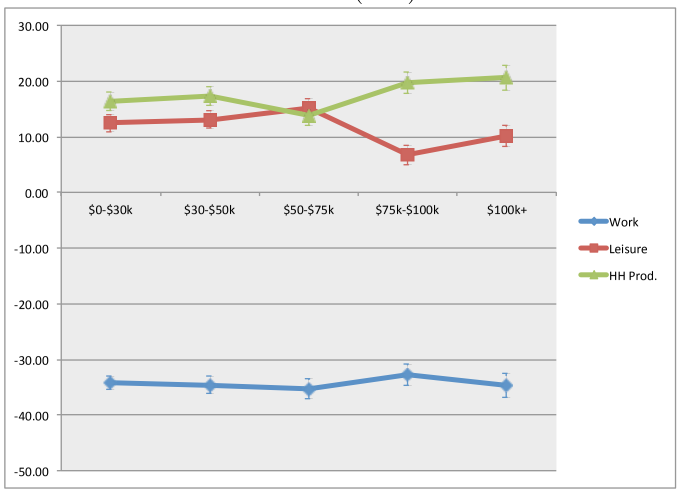
Unreported regressors include education, black and hispanic indicators for both partners, as well as controls for day of week, month, year and state.

Bootstrapped standard errors reported.

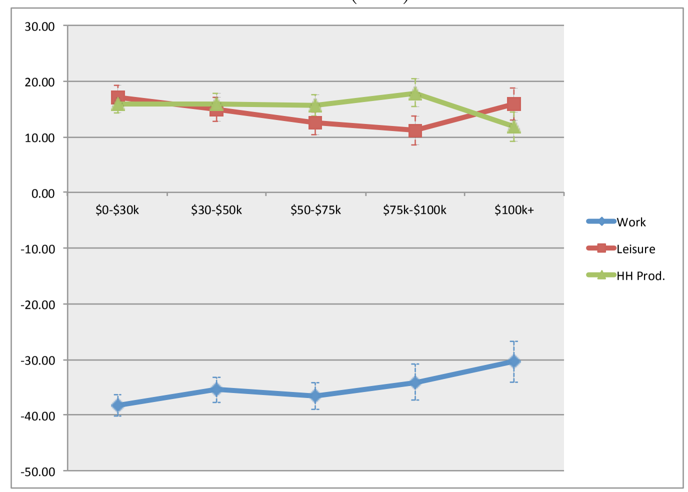
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4.1: **Time Use Effects of Full Employment to Unemployment**

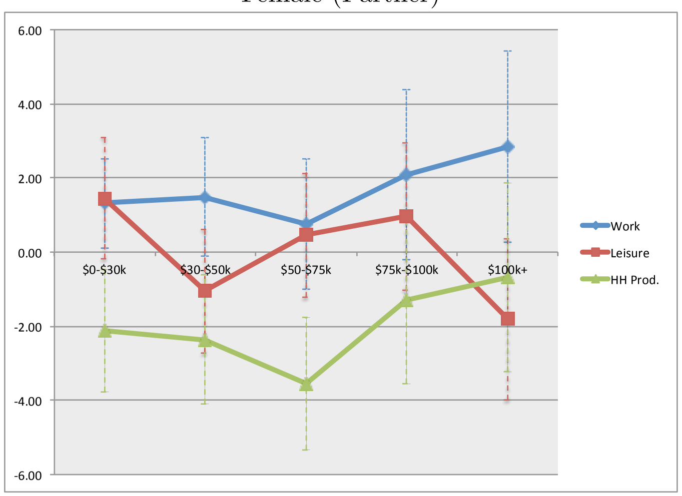
Female (Self)



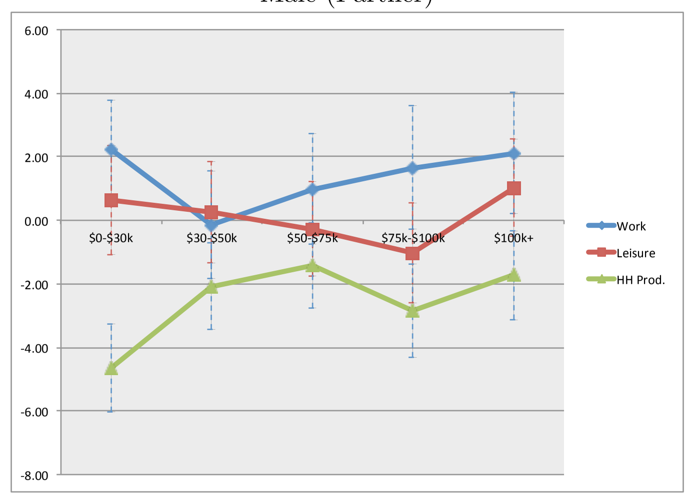
Male (Self)



Female (Partner)



Male (Partner)



Hours per week change in each activity

Table 4.17: **Marginal Effects of Partner's Time Use on Female Time Use**

	Work		Leisure		HH Prod.	
	OLS	CRAGG	OLS	CRAGG	OLS	CRAGG
WEEKDAY						
Partner Work	**4.86**	-1.29	-2.86	**-4.25**	1.22	0.74
	(2.05)	(3.13)	(1.85)	(1.94)	(2.07)	(2.12)
Partner Leisure	3.91	-6.77	2.63	-3.55	-3.76	-2.10
	(3.46)	(5.96)	(3.13)	(3.11)	(3.50)	(2.12)
Partner HH Production	**9.24**	6.18	**-6.72**	-3.47	-2.86	-5.50
	(3.68)	(4.58)	(3.32)	(4.22)	(3.71)	(4.03)
WEEKEND						
Partner Work	-5.18	**-12.70**	7.56	4.06	1.06	-6.58
	(5.02)	(3.75)	(5.02)	(4.80)	(5.11)	(5.85)
Partner Leisure	-4.59	**-14.04**	**19.74**	**14.99**	**-12.00**	**-20.33**
	(4.69)	(4.97)	(5.97)	(4.91)	(6.06)	(6.09)
Partner HH Production	**11.70**	4.14	10.92	5.19	**-16.62**	**-28.30**
	(5.35)	(5.44)	(6.78)	(6.47)	(6.90)	(7.34)

Estimates report the effect (in minutes per day) of a one hour per day increase of partner time use on own time use.
OLS and bootstrapped Cragg standard errors reported.
Bolded estimates are significant at the 95% level.

Table 4.18: **Marginal Effects of Partner's Time Use on Male Time Use**

	Work		Leisure		HH Prod.	
	OLS	CRAGG	OLS	CRAGG	OLS	CRAGG
WEEKDAY						
Partner Work	**11.10**	0.75	-0.62	-3.94	**-7.26**	**-5.15**
	(2.95)	(3.79)	(2.47)	(2.33)	(2.20)	(2.08)
Partner Leisure	**12.42**	-7.71	0.67	-10.35	**-12.06**	-4.59
	(6.30)	(7.61)	(5.28)	(6.42)	(4.69)	(4.30)
Partner HH Production	**16.14**	8.64	-0.37	-0.25	**-13.44**	**-13.30**
	(4.22)	(4.62)	(3.53)	(4.07)	(3.14)	(2.74)
WEEKEND						
Partner Work	**22.08**	13.23	0.64	-2.91	-8.70	**-19.64**
	(6.78)	(7.21)	(7.200	(7.23)	(6.24)	(5.37)
Partner Leisure	**25.86**	19.24	11.34	6.77	**-26.34**	**-37.39**
	(10.26)	(10.48)	(10.80)	(11.77)	(9.36)	(9.91)
Partner HH Production	**21.06**	10.66	6.18	1.16	-16.92	**-34.07**
	(10.20)	(10.41)	(10.80)	(10.42)	(9.36)	(8.51)

Estimates report the effect (in minutes per day) of a one hour per day increase of partner time use on own time use.

OLS and bootstrapped Cragg standard errors reported.

Bolded estimates are significant at the 95% level.

Table 4.19: **OLS Estimates on Activity Time of Females with Predicted Partner Time Use**

(Minutes per day spent in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.n	Work	Leisure	HH Prod.
FT employment (self)	400.6***	-129.1***	-213.9***	78.01***	-55.68***	-14.80***
	(3.735)	(3.378)	(3.775)	(3.424)	(4.361)	(4.434)
PT employment (self)	200.7***	-72.11***	-105.7***	67.38***	-35.39***	-28.80***
	(4.015)	(3.631)	(4.059)	(3.635)	(4.630)	(4.708)
Unemployed (self)	19.11*	-2.910	-13.74	4.388	-11.06	9.606
	(7.574)	(6.851)	(7.657)	(6.308)	(8.036)	(8.170)
Pred. Partner Work Time	0.0810*	-0.0477	0.0203	-0.0864	0.126	0.0176
	(0.0341)	(0.0309)	(0.0345)	(0.0657)	(0.0837)	(0.0851)
Pred. Partner Leisure Time	0.0651	0.0438	-0.0626	-0.0765	0.329***	-0.200*
	(0.0577)	(0.0522)	(0.0583)	(0.0781)	(0.0995)	(0.101)
Pred. Partner HH Prod. Time	0.154*	-0.112*	-0.0477	0.195*	0.182	-0.277*
	(0.0613)	(0.0554)	(0.0619)	(0.0891)	(0.113)	(0.115)
Male Partner	-72.42***	-0.774	64.78**	-19.11	-2.877	31.49
	(19.96)	(18.05)	(20.18)	(17.23)	(21.95)	(22.32)
Age	1.662	-2.737**	7.375***	-1.688	-3.283**	7.837***
	(1.140)	(1.031)	(1.152)	(0.954)	(1.215)	(1.235)
Age (partner)	-1.457	0.0972	0.539	-1.037	-2.177	3.433*
	(1.189)	(1.076)	(1.203)	(1.144)	(1.457)	(1.482)
Age^2	-0.0255*	0.0436***	-0.0734***	0.0118	0.0452***	-0.0752***
	(0.0115)	(0.0104)	(0.0116)	(0.00967)	(0.0123)	(0.0125)
Age^2 (partner)	0.0165	-0.00654	-0.00144	0.0128	0.0131	-0.0270
	(0.0118)	(0.0107)	(0.0120)	(0.0114)	(0.0145)	(0.0147)
Any HH children	-8.323	-16.27***	44.84***	-1.544	-25.68***	35.56***
	(4.473)	(4.046)	(4.522)	(3.805)	(4.847)	(4.928)
Child age 5 or under	-19.50***	-24.76***	65.64***	-8.605	-39.30***	70.99***
	(4.819)	(4.359)	(4.872)	(5.315)	(6.771)	(6.884)
Child age10 or under	-9.373	-16.87***	36.47***	-14.96**	-15.56*	41.34***
	(5.193)	(4.697)	(5.250)	(5.273)	(6.717)	(6.830)
Observations	15758	15758	15758	15963	15963	15963

Unreported regressors include education, black and hispanic indicators for both partners, as well as controls for day of week, month, year and state.

Standard errors in parentheses

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

Table 4.20: **OLS Estimates for Activity Time of Males with Predicted Partner Time Use**

(Minutes per day spent in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment (self)	436.6***	-230.4***	-130.6***	124.5***	-118.6***	4.242
	(6.576)	(5.507)	(4.891)	(8.346)	(8.800)	(7.640)
PT employment (self)	232.8***	-150.0***	-68.23***	97.86***	-90.56***	0.446
	(8.418)	(7.049)	(6.261)	(8.296)	(8.746)	(7.593)
Unemployed (self)	46.73***	-83.04***	42.63***	12.81	-50.17***	49.59***
	(10.53)	(8.815)	(7.829)	(10.57)	(11.14)	(9.675)
Pred. Partner Work Time	0.185***	-0.0103	-0.121***	0.368**	0.0106	-0.145
	(0.0492)	(0.0412)	(0.0366)	(0.113)	(0.120)	(0.104)
Pred. Partner Leisure Time	0.207*	0.0111	-0.201*	0.431*	0.189	-0.439**
	(0.105)	(0.0880)	(0.0782)	(0.171)	(0.180)	(0.156)
Pred. Partner HH Prod. Time	0.269***	-0.00610	-0.224***	0.351*	0.103	-0.282
	(0.0704)	(0.0589)	(0.0523)	(0.170)	(0.180)	(0.156)
Male Partner	-35.53	11.81	1.989	-5.637	-32.99	27.44
	(27.74)	(23.23)	(20.63)	(25.83)	(27.24)	(23.64)
Age	-0.114	-2.365*	3.994***	1.229	-3.442*	6.031***
	(1.384)	(1.159)	(1.030)	(1.451)	(1.529)	(1.328)
Age (partner)	1.082	1.047	0.521	-2.981	0.379	1.707
	(1.488)	(1.246)	(1.107)	(1.985)	(2.093)	(1.817)
Age^2	-0.00737	0.0304**	-0.0406***	-0.00540	0.0329*	-0.0618***
	(0.0136)	(0.0114)	(0.0101)	(0.0138)	(0.0145)	(0.0126)
Age^2 (partner)	-0.0127	-0.0101	0.00342	0.0163	0.000724	-0.00710
	(0.0155)	(0.0129)	(0.0115)	(0.0211)	(0.0222)	(0.0193)
Any HH children	-5.226	-15.45**	16.42***	2.370	-3.678	8.608
	(6.519)	(5.459)	(4.848)	(8.738)	(9.213)	(7.998)
Child age 5 or under	-11.06	-10.67	39.63***	-10.69	-21.46	44.48***
	(7.804)	(6.535)	(5.804)	(13.99)	(14.75)	(12.81)
Child age10 or under	-10.66	-14.05*	32.53***	-15.68	-24.09*	35.84***
	(6.973)	(5.839)	(5.186)	(9.280)	(9.784)	(8.494)
Observations	14246	14246	14246	14250	14250	14250

Unreported regressors include education, black and hispanic indicators for both partners, as well as controls for day of week, month, year and state.

Standard errors in parentheses

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

Table 4.21: **Cragg Estimates on Activity Time of Females with Predicted Partner Time Use**

(Minutes per day spent in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment (self)	381.6***	-131.1 ***	-205.1***	123.0 ***	-54.77***	-11.60 *
	(15.9)	(3.61)	(3.74)	(6.99)	(4.22)	(4.93)
PT employment (self)	257.3***	-64.69***	-84.48***	114.7***	-34.25 ***	-26.30***
	(15.14)	(3.50)	(3.20)	(8.80)	(4.47)	(4.29)
Unemployed (self)	37.88	-2.30	36.73 ***	13.00	-9.86	12.65
	(21.22)	(6.55)	(7.17)	(15.76)	(8.26)	(7.60)
Pred. Partner Work Time	-0.0215	-0.0708*	0.0123	-0.212**	0.0677	-0.110
	(0.0522)	(0.0324)	(0.0353)	(0.0624)	(0.0800)	(0.0975)
Pred. Partner Leisure Time	-0.113	-0.0592	-0.0349	-0.234 *	0.250**	-0.339**
	(0.0994)	(0.0518)	(0.0353)	(0.083)	(0.082)	(0.101)
Pred. Partner HH Prod. Time	0.103	-0.0579	-0.0917	0.0690	0.0865	-0.472***
	(0.076)	(0.0703)	(0.0671)	(0.0907)	(0.108)	(0.122)
Male Partner	-55.29**	-0.638	110.9 **	-1.458	0.529	38.34
	(20.97)	(24.20)	(31.99)	(15.43)	(31.98)	(31.46)
Age	4.597 ***	-1.445	6.510***	-1.343	-2.906**	8.530***
	(1.31)	(1.030)	(1.041)	(1.175)	(1.106)	(1.296)
Partner's Age	-1.985	-0.484	1.027	-0.300	-1.824	4.242*
	(1.175)	(0.995)	(0.985)	(0.984)	(1.642)	(1.503)
Age^2	-0.0596 ***	0.0259	-0.0588 ***	0.00953	0.0406***	-0.0825***
	(0.0138)	(0.0100)	(0.0138)	(0.01066)	(0.01388)	(0.0094)
Partner Age^2	0.0230	0.0000894	-0.00588	0.00597	0.00953	-0.0343
	(0.0131)	(0.0114)	(0.0096)	(0.0133)	(0.0132)	(0.0185)
[.5em]Any HH Child	-11.54 **	-18.91***	56.47***	-1.894	-24.29 ***	39.30***
	(4.062)	(3.996)	(5.184)	(3.294)	(4.799)	(5.090)
Child aged 5 or less	-18.41***	-30.46***	62.25***	-6.468	-39.26***	72.41 ***
	(4.680)	(5.306)	(4.717)	(4.573)	(7.02)	(7.98)
Child aged 10 or less	-10.96 *	-23.15 ***	41.83***	-13.88**	-15.61*	42.48 ***
	(5.18)	(4.39)	(4.32)	(4.71)	(6.60)	(7.66)
N	15758	15758	15758	15963	15963	15963

Unreported regressors include education, black and hispanic indicators for both partners, as well as controls for day of week, month, year and state.

Bootstrapped standard errors reported in parentheses.

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

Table 4.22: **Cragg Estimates on Activity Time of Males with Predicted Partner Time Use**

(Minutes per day spent in each activity)

	Weekday			Weekend		
	Work	Leisure	HH Prod.	Work	Leisure	HH Prod.
FT employment (self)	443.4***	-186.9***	-112.0***	222.2 ***	-111.7***	8.73
	(26.73)	(5.025)	(3.74)	(28.05)	(7.15)	(7.58)
PT employment (self)	281.6 ***	-106.4***	-47.49***	198.4***	-83.33***	3.45
	(28.21)	(7.10)	(5.70)	(26.86)	(10.32)	(7.51)
Unemployed (self)	58.08	-51.66***	20.23 ***	43.24	-42.52	49.43***
	(34.02)	(8.97)	(5.27)	(28.08)	(21.97)	(9.59)
Pred. Partner Work Time	0.0125	-0.0656	-0.0858*	0.221	-0.0484	-0.327***
	(0.063)	(0.0388)	(0.0347)	(0.1202)	(0.1204)	(0.090)
Pred. Partner Leisure Time	-0.129	-0.173	-0.0765	0.321	0.113	-0.623***
	(0.127)	(0.107)	(0.0717)	(0.1746)	(0.196)	(0.1652)
Pred. Partner HH Prod. Time	0.144	-0.00412	-0.222 ***	0.178	0.0193	-0.568***
	(0.077)	(0.0679)	(0.0457)	(0.1734)	(0.1736)	(0.1418)
Male Partner	-20.98	20.47	-4.471	3.892	-30.99	31.93
	(33.60)	(31.02)	(22.312)	(26.22)	(40.18916)	(23.2702)
Age	2.255	-1.752	3.148 **	1.457	-3.271 *	7.228***
	(1.380)	(1.432)	(1.432)	(1.074)	(1.559)	(1.2013)
Age (Partner)	2.259	0.228	1.507	-1.341*	0.725	3.250
	(1.581)	(1.173)	(1.024)	(1.669)	(1.987)	(1.945)
Age^2	-0.0361*	0.0225	-0.0303**	-0.00782	0.0305	-0.0736 ***
	(0.0155)	(0.0119)	(0.0099)	(0.0150)	(0.0122)	(0.0136)
Partner Age^2	-0.0237	-0.000024	-0.00700	0.00119	-0.00178	-0.0212
	(0.0195)	(0.01142)	(0.0103)	(0.02308)	(0.0204)	(0.017)
Any HH Child	-10.90	-18.32 **	20.61***	3.558	-2.451	14.92 *
	(6.984)	(5.834)	(4.60)	(8.7486)	(9.196)	(7.201)
Child aged 5 or less	-14.35	-19.26 **	43.46***	-3.594	-19.88	53.36 ***
	(7.978)	(6.22)	(6.234)	(12.810)	(13.226)	(13.58)
Child aged 10 or less	-15.21*	-22.50**	39.59***	-9.082	-23.64*	40.76 ***
	(6.10)	(6.628)	(4.74)	(7.943)	(9.627)	(7.376)
N	14246	14246	14246	14250	14250	14250

Unreported regressors include education, black and hispanic indicators for both partners, as well as controls for day of week, month, year and state.
Bootstrapped standard errors reported in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

CHAPTER V

Conclusion

This dissertation provides important findings into the impact of certain governmental policies and behavior related to time use. The first finding is how difficult it is to show that place-based economic development programs are sufficient in providing an economic boost to rural areas. To be certain, the time frame on the study was limited and only looked at federal based programs, but a variety of national economic trends and regional economic development theory suggest that such programs are not likely to be successful. That said, the organizational incentives provided by the Enterprise Community program may have generated sufficient regional institutional development in these areas that can provide long term benefits.

Another finding revolved around the empirical result that higher levels of public transportation attractiveness, while certainly leading to more time spent in public transportation, does not lead to lower car-based commuting time. In addition, frequently policies which seek to improve public transportation attractiveness and those which may raise gas prices can have dampening effects on each other. That is, the marginal effect of each at lowering car usage or increasing public transportation usage can be reduced by the other's impact. Transportation policy, thus, should be made keeping in mind these interaction effects and the strong difficulty of inducing switching to public transportation from driving for commuting based activities.

The final paper utilizes time use data to examine the impact of spousal unemployment and are consistent with other studies in finding a very small, but statistically significant impact of about an hour per week added worker effect. I also construct estimates of partner spousal time use where data do not exist to calculate marginal impacts, finding strong leisure complementarity between partners and some substitutability of household production. These findings are all consistent with previous research on the topic and are confirmed with the American Time Use Survey data.

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