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COMMUTING TIME AND HOUSEHOLD RESPONSIBILITIES: EVIDENCE USING PROPENSITY SCORE MATCHING*

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ABSTRACT. We examine the relationship between individual commuting behavior and household responsibilities, with a focus on gender differences in that relationship. Using the Dutch Time Use Survey for the years 2000 and 2005, we analyze the relationship between commuting time, home production, and childcare. To deal with reverse causality, we use Propenstity Score Matching techniques to obtain imputed data for individuals. We find that the effect of home production on commuting time for women is more than double that for men, while childcare time has an effect on women's commuting behavior only. Our results shedding light on the Household Responsibility Hypothesis.

1. INTRODUCTION

In this paper, we examine the relationship between commuting time and the time devoted to both home production and childcare, with a focus on gender differences. We use the Dutch Time Use Survey (DTUS) for the years 2000 and 2005, which allows us to analyze the time devoted to commuting, home production, and childcare during the day, and provides information for seven days of the week for each individual. To deal with potential endogeneity, we use Propensity Score Matching (PSM) techniques to obtain imputed data for individuals. The fact that individuals report their daily activities in their own words, makes these surveys extremely helpful, as has been shown in Gimenez-Nadal and Molina (2014), given that individual perceptions determine whether the activity is considered to be commuting, or not.

Recent studies have shown that most household responsibilities (e.g., time devoted to home production and childcare) continue to be carried out by women (Aguiar and Hurst, 2007; Gimenez-Nadal and Sevilla, 2012), and evidence from time use surveys in developed countries shows that there remains a gender gap in commuting time (men devote more time to this activity), and that this difference has remained relatively constant over time. More specifically, Figure 1 shows the average time devoted to commuting by men and women, in recent decades, in the Netherlands, the United Kingdom, and the United

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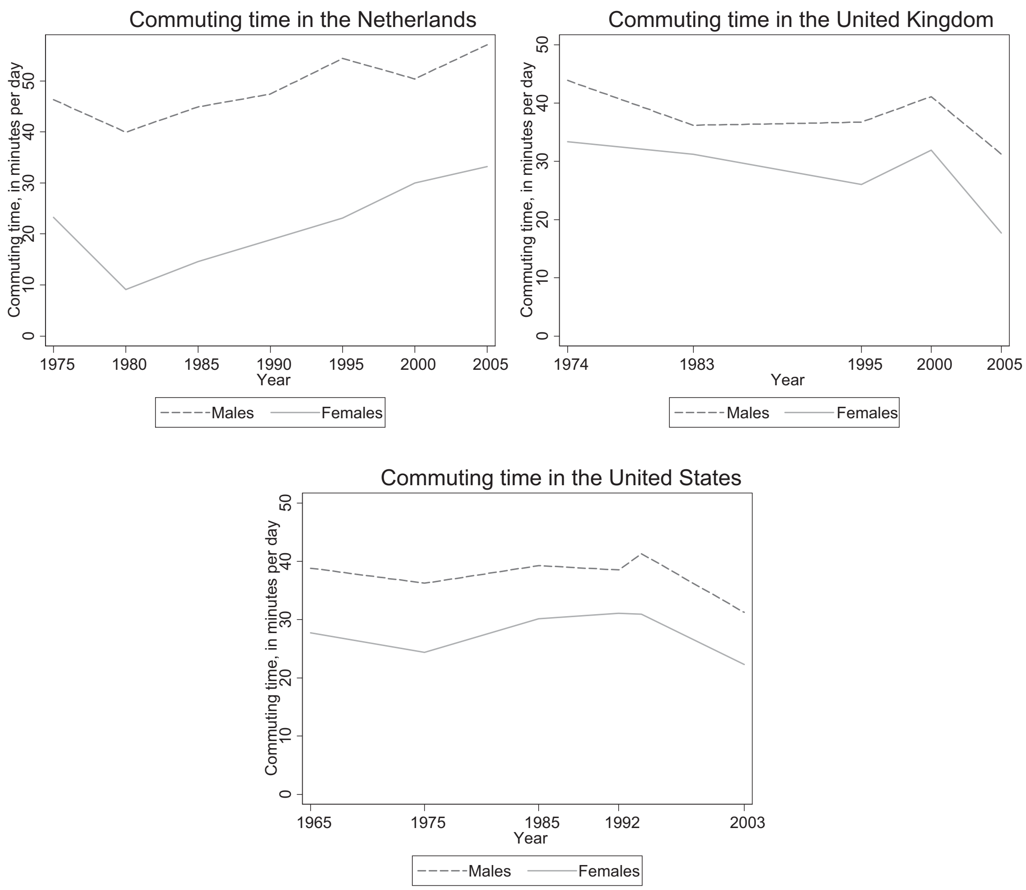


Notes: Source is the Multinational Time Use Study, version W58, accessed in November 2012. Sample consists of male and female respondents who participate in the labor market, from the Netherlands (1975, 1980, 1985, 1990, 1995, 2000, and 2005), the United Kingdom (1974, 1983, 1995, 2000, and 2005), and the United States (1965, 1975, 1985, 1992, 1994, and 2003). *Commuting* is the time devoted to "travel to or from work." We calculate the average time devoted to commuting by country, survey, and gender, and demographic weights included in the survey are used.

FIGURE 1: Time Devoted to Commuting in the Netherlands, the United Kingdom, and the United States by Gender.

States, obtained from an analysis of the Multinational Time Use Study (MTUS). We observe that the average commuting time of women is well below that of men (23.87, 15.58, and 8.93 fewer daily minutes on average for women compared to men, in the respective countries), representing differences of 72 percent, 77 percent, and 26 percent of one standard deviation of commuting time for women in the Netherlands, the United Kingdom, and the United States, respectively. Additionally, these differences have remained relatively constant in two of the three countries, and have increased in the U.K.

The analysis of commuting behavior and its associated gender differentials is important for several reasons. For instance, Kahneman et al. (2004) and Kahneman and Krueger (2006) show that time spent in commuting ranks among the lowest activities in terms of the "instant enjoyment" obtained by individuals. There are also psychological costs associated with travel (Koslowsky, Kluger, and Reich 1995; Kahneman et al., 2004;

Stutzer and Frey, 2008), which include increased blood pressure, physical disorders, and anxiety. Furthermore, Kwan and Kotsev (2015) study patterns of commuting time in the city of Sofia (Bulgaria), and find that women tend to spend more time in commuting, which is disadvantageous to them because it is associated with reduced access to urban opportunities. Also, individuals may choose to work closer to home in order to fulfill their household responsibilities, which can affect their job search area and lead them to having less well-paid jobs. Short-distance commuters may have limited access to a wider range of job opportunities (Dyck, 1989, 1990; England, 1993; MacDonald, 1999; Rapino, 2008; Wheatley, 2013).

The literature on the effect of gender on commute duration is inconclusive. Some studies have shown that commuting differences by gender change little, historically, with women's trip lengths remaining substantially below those of men (see, among others, Kain, 1962; Rosenbloom, 1978; Giuliano, 1979). Crane (2007) shows that, in the U.S., after controlling for other sources of difference, such as demographics and community features, the average woman's trip to work differs markedly from that of the average man.[1] Iwata and Tamada (2014) show that time spent commuting by married Japanese women follows a backward-bending pattern, as there is a trade-off between commute time and the hours devoted to housework as wage rates increase. Sandow and Westin (2010) find that Swedish women have a shorter commute than men, regardless of employment sector, education level, or family situation, indicating that the gender role and the daily time constraints of women impose stricter limitations on women's geographical labor mobility. But other studies have challenged the idea that the transportation needs of women are different from those of men. Doyle and Taylor (2000) argue that commute times converge for gender, among other variables, as early as the mid-1990s. Gossen and Purvis (2005) report that San Francisco journey-to-work times in 2000 were the same for women and men in all age groups, except for those in the 50+ age group, and Vandersmissen, Thériault, and Villenueve (2004) show that commute distances in the Quebec Metropolitan Area also converge when controlling for type of household or for the presence of children.

The debate about gender differences in commuting behavior is reflected in a range of theories. Rational utility theorists argue that women's lesser attachment to the labor force is behind their shorter commute times, and that these gender differences will tend to diminish in the future. Others contend that women's shorter commutes are an outcome of the constraints society puts on women, at home and at work, with these being divided into those who attribute the source of the difference to the problem of gender discrimination in the labor market, and those who attribute it to women's household responsibilities, thus hypothesizing that the disproportionate burden of household responsibility on women requires shorter commute times, and makes it difficult for them to work any distance away from home (this has come to be known as the Household Responsibility Hypothesis (HRH)).

Considering the HRH issue, Turner and Neimeier (1997) review prior evidence of the relationship between commuting and household responsibility, and find that the research evaluating the degree to which this gender differential in commuting can be explained by the division of labor in the household has produced mixed results, despite that the authors do find evidence in favor of the HRH. We focus here on testing the HRH, and offering new empirical findings. To that end, we use the sample of working individuals from the DTUS of 2000 and 2005 to empirically address the relationship between commuting time and the time devoted to both home production and childcare activities. One substantial advantage

[1]Other recent studies of gender differences in commute time are Blumen (1994), Lee and McDonald (2003), and Mok (2007).

of the DTUS over other time use surveys, such as the American, the Australian, and the British, is that there is time use information for seven consecutive days for each individual, allowing us to take into account potential variations of commuting times on different days. In our empirical analysis, we take into account that the time devoted to commuting, home production, and childcare are choices workers make, and we thus propose the use of a matching strategy (PSM) to deal with the potential endogeneity between commuting time and household responsibilities.

Our results show that, after potential endogeneity is taken into account, one additional hour of home production is associated with a decrease in commuting time for both men and women who are childless, although this negative relationship is more pronounced for women, by a factor close to two. Given that childless women devote comparatively more time to home production than childless men, this evidence is consistent with women having shorter commutes. Additionally, considering men and women with at least one child under 18, we find that home production and childcare time affects only women's commuting time, while men's home production and childcare times do not seem to affect their time devoted to commuting. This last result indicates that household responsibilities affect women's commuting time but not men's commuting time when they have children, which could explain why women have shorter commutes. All the evidence presented here supports the HRH.

Our contribution to the literature is threefold. First, as argued by Crane (2007), understanding the effect of women's roles on their commute lengths may help predict future housing and workplace location preferences, depending on their household responsibilities and lifestyles, and can also help predict future location decisions of employers who want to employ women, who may or may not be spatially restricted. Our study proves relevant to this issue. Second, it may be important for future transportation planning, regarding the varied demands of transportation modes for women and men. For instance, it could be that, due to their household responsibilities, women may be more likely than men to use public transport (Schulz and Gilbert, 1996; Doyle and Taylor, 2000; Hamilton and Jenkins, 2000; Sánchez de Madariaga, 2013). Third, we introduce time use surveys, and the use of PSM methods, as an alternative data source to analyze individual commuting behavior. As has been shown in Gimenez-Nadal and Molina (2014), the use of this type of survey, together with the PSM method, are helpful in analyzing the relationships between commuting time and other uses of time.

The rest of the paper is organized as follows. Section 2 reviews the factors that have been identified as relating to the commuting behavior of individuals. Section 3 describes the data. Section 4 describes our empirical strategy, Section 5 presents the results, and Section 6 sets out our main conclusions.

2. LITERATURE REVIEW

In the study of commuting behavior, it is usually distance and/or time that are analyzed. However, we must acknowledge that those two concepts (distance and time) are not equal, nor are they measured in the same way. For instance, Rietveld et al. (1999) argue that, in the measurement of travel distances (by car), actual distances are not normally known and information on the "shortest" route is used instead. When actual travel times are measured, commuters tend to include ancillary activities such as walking to the final destination, and while shorter commute times tend to be underestimated, relatively longer commute times tend to be overestimated (Bovy and Stern, 1990). Thus, despite that both concepts are related, a distinction between commuting time and distance must be made. An example of the separation between travel time and distance is shown in the Alonso-Muth monocentric model (Alonso, 1968; Muth, 1969), where differences in both commuting distance and travel time are important in determining household location. According to this model, travel distance enters via direct travel costs, while travel time enters via the opportunity cost of time.

Furthermore, despite that commuting time and distance are related, the relationship depends on the mode of transport, among other factors. More people in Europe (Orfeil and Bovy, 1993; Kenworthy and Laube, 1999; Schwanen, Dieleman, and Dijst, 2002) and the Netherlands (Susilo and Maat, 2007) use bicycles than do commuters in the U.S., who make much more use of cars, and thus cover greater distances, in less time, than their European counterparts. On the other hand, personal characteristics may also affect the time-distance relationship, as some prefer faster routes, on highways, that will involve longer distances. Studies have identified several potential influences on commuting habits, which can be grouped in three basic categories: microeconomic, land use/geographical, and macroeconomic factors. The microeconomic and land use/geographical variables are the most commonly analyzed characteristics, while the analysis of macrovariables, such as the use of Gross Domestic Product (GDP) or (lagged) changes in GDP to make predictions, or as a control variable, is somewhat limited in the literature (Dargay and Gately, 1997; Johansson, Klaesson, and Olsson, 2002; Östh and Lindgren, 2012).

For the land use/geographical variables, studies have found a negative relationship between commuting and population/residential density (Rouwendal and Nijkamp, 2004; Schwanen, Dieleman, and Dijst, 2004; Susilo and Maat, 2007; Sandow, 2008; Dargay and Clark, 2012) and job density (Johansson et al., 2002; Rouwendal and Nijkamp, 2004). Factors that may condition the commuting behavior of individuals are the urban/rural residence (Schwanen, Dieleman, and Dijst, 2004; Susilo and Maat, 2007; Östh and Lindgren, 2012), residential region (Pucher and Renne, 2003; Sandow and Westin, 2010), housing prices (Rouwendal and Nijkamp, 2004), and intensity of land use (Rouwendal and Nijkamp, 2004; Van Acker and Witlox, 2011), among others.[2] However, Schwanen, Dieleman, and Dijst (2003) show that the characteristics of individuals and their positions in the household have a stronger influence on commuting times by car than the urban structure in which people live and work.

The sociodemographic characteristics of individuals, such as gender, age, level of education, personal income, home ownership, or car availability/ownership, have all been considered as influencing the commuting behavior of individuals. In the specific case of commuting times, higher wage rates are associated with longer commuting times. This can be seen, for example, in the converging commuting times of younger cohorts, compared with older cohorts, with the former also having converging wage rates (Law, 1999; Crane, 2007). In the absence of information of wage rates, personal income and education can be used as proxies, and have been found to have a positive influence on commuting times (Rouwendal and Nijkamp, 2004; Dargay and Van Ommeren, 2005; Susilo and Maat, 2007; Sandow, 2008; Sandow and Westin, 2010; Dargay and Clark, 2012). Furthermore, full-time workers will usually have higher wage rates than part-time workers, which may explain their longer commuting times (McQuaid and Chen, 2012).[3] Furthermore, dual-earner households are positively related to commuting time (Flowerdew, 1992;

[2]Despite the fact that household location choice models with commuting distance have been developed (e.g., DeSalvo, 1985; DeSalvo and Huq, 2005; Ng, 2008; Deding, Filges, and Van Ommeren, 2009), we consider the location choice as fixed.

[3]An additional factor that is related with commute (distance) is that of occupation, as longer commutes may mean the possibility of high-paid professional occupations. In this sense, it has been found that commute distances are longer for managers and professionals compared to other occupations (Shearmur, 2006; McQuaid, 2009; McQuaid and Chen, 2012; Walks, 2014). Unfortunately, there is no information on the occupation of the individuals, and thus we cannot control for this factor in our time use regressions.

Green, 1997; McQuaid and Chen, 2012), as home location may be chosen to minimize the joint travel, rather than a single trip to work. Home ownership, compared to renting (Deding, Filges, and Van Ommeren, 2009; Groot, de Groot, and Veneri, 2012; McQuaid and Chen, 2012) and car ownership (Pucher and Renne, 2003; Schwanen, Dieleman, and Dijst, 2004; Dargay and Clark, 2012; McQuaid and Chen, 2012) are two factors that have also been found to be positively related to the length of the commute.

Gender has been found to be related to lower commuting times (Hanson and Hanson, 1993; Turner and Neimeier, 1997; Sandow, 2008; Sandow and Westin, 2010; Dargay and Clark, 2012; Groot, de Groot, and Veneri, 2012; McQuaid and Chen, 2012), and several explanations have addressed gender differences in commuting behavior. First, it could be that differences in the sociodemographic characteristics of men and women explain the gender gap in commuting distance and time, as higher income and education are positively related to commuting distance. In this sense, the difference could be because women earn lower wages (Waldfogel, 2007). However, and despite that the gender difference in commuting decreases when one controls for income and occupation (Singell and Lillydahl, 1986; Hanson and Johnston, 1985; Sandow and Westin, 2010), the difference does not disappear. A second factor is geographical, as there are gender-segregated labor markets in which women are concentrated in female-dominated occupations. To the extent that these female-dominated occupations are more evenly distributed, compared to male-dominated occupations, women have greater possibilities of finding a job closer to home, with a shorter commute (Hanson and Johnston, 1985; Hanson and Pratt, 1995).

The third and main hypothesis of this paper is related to social roles: social roles for men and women differ, and women must adapt their commuting patterns to their chores at home, accepting jobs closer to home (Turner and Neimeier, 1997; Sandow and Westin, 2010). Thus, greater household responsibilities for females require them to commute less, giving rise to the HRH (Johnston-Anumonwo, 1992; Turner and Neimeier, 1997). Prior literature has used household type, marital status, the presence of (young) children, and/or other household members, to test this hypothesis (Hanson and Johnston, 1985; Johnston-Anumonwo, 1992; Lee and McDonald, 2003; McQuaid and Chen, 2012), comparing commuting time and length, the number of stops and/or time in other activities. Others have used the residential location patterns of households (Hanson and Johnston, 1985; Jun and Kwon, 2015), the gendered analysis of labor supply and/or commuting patterns (Gutiérrez-i-Puigarnau and Van Ommeren, 2010; Compton and Pollak, 2014), and the geo-visualization of commuting behavior (Kwan, 1999; Kwan and Kotsev, 2015). But in the specific case of time use surveys, their recent development means that such surveys have not been used before, especially in the approach used in this paper, as we analyze the time devoted to commuting, home production, and childcare, while simultaneously dealing with potential endogeneity.

At the root of the HRH we may find space-time constraints on activities as contributory factors in gender differentials in commuting time. According to this time-geographic perspective, out-of-home activities have specific space-time requirements and relationships with other activities (Kwan, 2000), and prior studies have found that the rigidity of space-time constraints differ from men to women (Kwan, 1999, 2000; Schwanen, Kwan, and Ren, 2008). Certain in-home activities are more restrictive as they must be done in a daily basis ("routine" activities), while others are more sporadic. The literature has shown that women specialize in routine (e.g., cooking, childcare) home production activities, while men specialize in activities (e.g., car maintenance, home maintenance) that are more sporadic (Cohen, 1998; Hersch and Stratton, 2002; Sevilla, Gimenez-Nadal, and Fernandez, 2010). Thus, the space-time requirements of household chores done by men and women are different, which affects the ability to perform out-of-home activities differently.

Regarding the data sources used to analyze commuting patterns, National Travel Surveys have traditionally been used for the analysis of commuting patterns of households in various countries. For example, Susilo and Maat (2007) analyze trends in commuting behavior in the Netherlands using the Dutch National Travel Surveys, and the influence of the built environment on trends in commuting journeys. These surveys capture a full picture of commuting behavior of individuals and households, and they include information on time and distance in commuting as well as the speed of the journey, the number of stops, and whether commuters left their home municipalities. In comparison with time use surveys, these National Travel Surveys are superior in terms of the information reported for commuting journeys, since time use surveys only provide information on duration, departure and arrival time, and mode of transport. However, time use surveys can serve as a complement to National Travel Surveys, as shown by Kitamura and Fuji (1997), who contend that time-use surveys should be used in order to continue developing transportation planning methodologies. The use of time-use surveys in transportation research has become a common practice, as shown by Jara-Díaz and Rosales-Salas (2015). Furthermore, time-use surveys are important in analyzing the relationship between commuting time and time devoted to noncommuting activities, which includes housework, childcare, and leisure. Other alternative methodologies used to analyze commuting behavior are panel data on commuting behavior (Gutiérrez-i-Puigarnau et al., 2010) and geo-visualization (Kwan, 2004; Kwan and Lee, 2004; Gershenson, 2013; Kwan and Kotsev, 2015).

3. DATA: THE DTUSs, 2000 AND 2005

The data used for the empirical analysis are drawn from the versions of the DTUS 2000 and 2005 included in the MTUS. The DTUS contains information on daily activities, gathered by means of the completion of a personal diary, and household and individual questionnaires. Both surveys were conducted in October of the reference year, and one member of the household, aged 12 or older, was selected to report information on daily activities during seven consecutive days. The diary time frame is 24 consecutive hours (from 12:00 a.m. until 12:00 a.m. the following day) and is divided into 15-minute intervals.

The MTUS is an *ex post* harmonized cross-time, cross-national, comparative time use database, coordinated by the Centre for Time Use Research at the University of Oxford. It is constructed from national randomly sampled time-diary studies, with common series of background variables, and total time spent in 41 activities (Gershuny, 2009). The MTUS provides us with information on individual time use, based on diary questionnaires in which individuals report their activities throughout the 24 hours of the day. The advantage of time-use surveys over stylized questions, such as those included in the databases ECHP, BHPS, and SOEP (where respondents are asked how much time they have spent, for example, in the previous week, or normally spend each week, on market work or home production) is that diary-based estimates of time use are more reliable and accurate than estimates derived from direct questions (Juster and Stafford, 1985; Robinson, 1985; Bianchi et al., 2000; Bonke, 2005; Yee-Kan, 2008).[4]

For the sake of comparison with prior studies (Aguiar and Hurst, 2007; Gimenez-Nadal and Sevilla, 2012), we restrict our sample to full-/part-time workers between the ages of 21 and 65 (inclusive). Our results can thus be interpreted as being “per working adult,” who are likely to commute to and from work. Additionally, given that households

[4]The MTUS has been widely used across the social sciences (Gershuny, 2000, 2009; Gershuny and Sullivan, 2003; Guryan et al., 2008; Gimenez-Nadal and Sevilla, 2011, 2012; Gimenez-Nadal and Molina, 2013).

have typically been defined as those formed by a couple and their children (Connelly and Kimmel, 2009; Gimenez-Nadal and Molina, 2013), we also restrict the sample to individuals who are the head of a household or his/her spouse/partner. The existing literature (Kalenkoski, Ribar, and Stratton, 2005; Guryan, Hurst, and Kearney, 2008) shows that the time devoted to childcare activities by men and women depends on their family status, with single parents devoting less time to their children. Our variables of interest refer to the daily time devoted to commuting, home production, and childcare, providing us with 739 male and 884 female respondents, and information at the individual level for the seven days of the week.[5]

Empirical Evidence

Table 1 shows the overall time devoted to *Commuting*, *Home Production*, and *Childcare* for all the working individuals in our sample, by gender. We observe that men devote 0.57, 1.81, and 0.33 hours per day to *Commuting*, *Home Production*, and *Childcare*, while women devote 0.30, 3.52, and 0.75 hours per day to those activities, respectively.[6] We find a gender difference in the time devoted to *Commuting* that is statistically significant at standard levels, with male workers devoting more time to this activity (0.27 more hours per day) compared to their female counterparts, consistent with the existing literature showing that men have longer commutes than women (Pazy, Salomon, and Pintzov, 1996; Turner and Neimeier, 1997; Plaut, 2006).[7] We also find a gender gap in *Home Production* and *Childcare* as females devote 1.70 and 0.42 more hours per day, respectively, to these activities, compared to their male counterparts, with such differences being statistically significant at standard levels. Thus, we find that working females devote less time to *Commuting* and more time to *Home Production* and *Childcare*, which is consistent with the HRH framework, within which women have shorter commutes because they have more household responsibilities. Additionally, differences in the time devoted to the three activities are also reflected in terms of participation in the activity, as the percentage of males doing *Commuting* on any given day is larger compared to females, while the opposite holds for *Home Production* and *Childcare*. Thus, males are 17.09 percentage points more likely to do *Commuting* on the day of the diary, while they are 13.39 and 10.68 percentage points less likely to do *Home Production* and *Childcare*, respectively. These differences indicate that men not only devote more time to *Commuting*, but are also more likely to commute, and the opposite holds for *Home Production* and *Childcare*.

[5]For the time devoted to *Commuting*, we use the information collected in the variable main63 "travel to or from work" of the MTUS, measuring the time devoted to Commuting during the reference day. For the time devoted to *Home Production*, we use the information collected in the variables main18 "food preparation, cooking," main19 "set table, wash/put away dishes," main20 "cleaning," main21 "laundry, ironing, clothing repair," main22 "home/vehicle maintenance/improvement," main23 "other domestic work," main24 "purchase goods," main26 "consume other services," main27 "pet care (other than walk dog)," main32 "adult care," main66 "child/adult care-related travel," and main67 "travel for shopping, personal or household care," and we sum the time devoted to all these activities. For the time devoted to *Childcare*, we use the information collected in the variables main28 "physical, medical childcare," main29 "teach, help with homework," main30 "read to, talk or play with child," and main31 "supervise, accompany, other childcare," and we sum the time devoted to these activities.

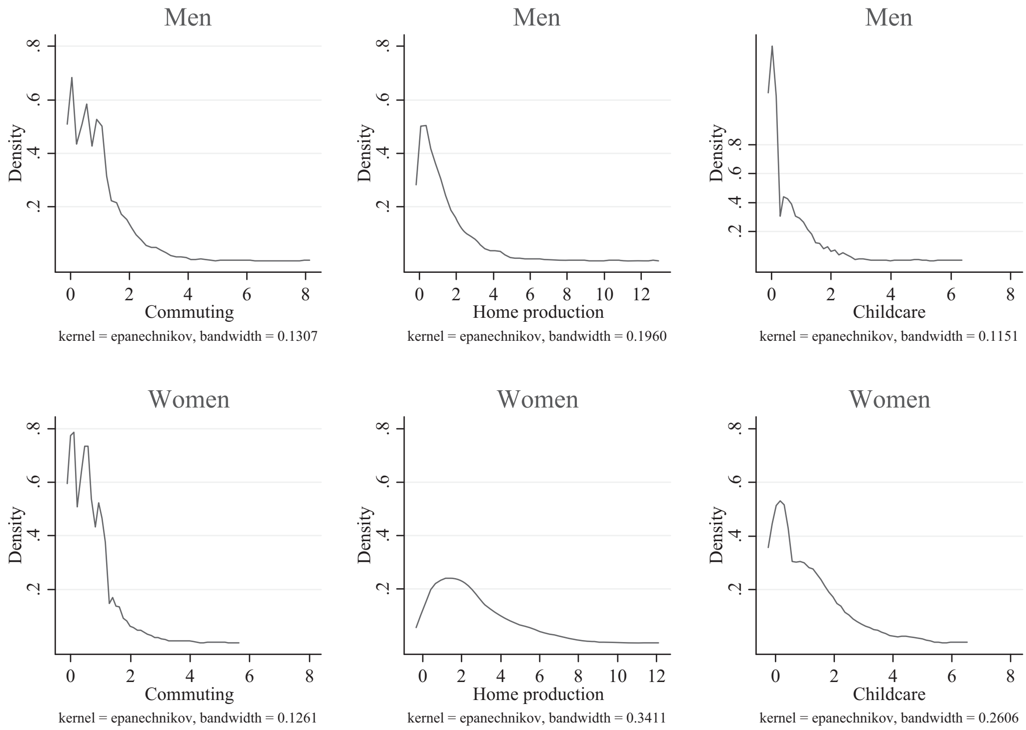
[6]We have used all the individuals in our sample to compute the average time in *Commuting* and *Home Production*. In the case of *Childcare* time, we use individuals with at least one child under 18 in the household.

[7]Diff. Men-Women measures the difference in the overall value of the variable for men and women, *P*-value diff. shows the *P*-value of a *t*-type test of equality of means. A *P*-value lower than 0.05 indicates that the difference between the mean values is statistically significant at standard levels.

TABLE 1: Sum Stats

	Men		Women			
	Mean	SD	Mean	SD	Diff Men-Women	*P*-Value Diff
Commuting						
Time	0.57	(0.51)	0.30	(0.37)	0.27	(0.00)
Participation	50.35	(29.54)	33.26	(28.54)	17.09	(0.00)
Home Production						
Time	1.81	(1.25)	3.52	(1.54)	−1.70	(0.00)
Participation	82.78	(22.56)	96.17	(10.07)	−13.39	(0.00)
Childcare						
Time	0.33	(0.61)	0.75	(1.14)	−0.42	(0.00)
Participation	24.52	(36.11)	35.20	(42.46)	−10.68	(0.00)
Demographics						
Age	42.29	(9.79)	40.90	(10.67)	1.39	(0.00)
Secondary education	0.35	(0.48)	0.47	(0.50)	−0.12	(0.00)
University education	0.48	(0.50)	0.39	(0.49)	0.09	(0.00)
Working full-time	0.89	(0.31)	0.32	(0.47)	0.57	(0.00)
Partner employed	0.55	(0.50)	0.69	(0.46)	−0.15	(0.00)
Number of children <18	0.86	(1.13)	0.80	(1.02)	0.06	(0.28)
Youngest child <5	0.18	(0.39)	0.19	(0.40)	−0.01	(0.54)
Youngest child 5–12	0.19	(0.39)	0.17	(0.38)	0.02	(0.41)
Youngest child 13–17	0.06	(0.24)	0.08	(0.27)	−0.01	(0.27)
At least one motorized vehicle at home	0.90	(0.30)	0.85	(0.35)	0.05	(0.00)
At least one computer at home	0.89	(0.32)	0.84	(0.37)	0.04	(0.01)
Household Income	29.96	(30.74)	25.64	(32.48)	4.32	(0.01)
Public sector	0.14	(0.35)	0.16	(0.36)	−0.01	(0.49)
Living in urban area	0.82	(0.38)	0.83	(0.38)	−0.01	(0.73)
Population density	878.41	(1011.85)	818.22	(913.19)	60.19	(0.21)
Housing prices	1.98	(0.38)	1.92	(0.39)	0.07	(0.00)
Amsterdam, Rotterdam, and the Hague	0.06	(0.25)	0.05	(0.22)	0.02	(0.19)
Drenthe	0.05	(0.21)	0.05	(0.23)	−0.01	(0.53)
Flevoland	0.03	(0.17)	0.04	(0.19)	−0.01	(0.31)
Friesland	0.04	(0.20)	0.06	(0.24)	−0.02	(0.12)
Gelderland en Zop	0.09	(0.28)	0.09	(0.29)	−0.01	(0.59)
Groningen	0.06	(0.23)	0.05	(0.22)	0.01	(0.52)
Limburg	0.04	(0.19)	0.04	(0.18)	0.00	(0.90)
Noord Brabant	0.16	(0.36)	0.15	(0.36)	0.01	(0.67)
Noord Holland	0.11	(0.31)	0.11	(0.32)	−0.01	(0.62)
Overijssel en Nop	0.09	(0.28)	0.08	(0.27)	0.01	(0.70)
Utrecht	0.09	(0.28)	0.07	(0.26)	0.02	(0.26)
Zeeland	0.02	(0.15)	0.02	(0.12)	0.01	(0.21)
N observations	739		884			

Notes: Sample consists of male and female respondents aged 21–65, who are the head of the household or the spouse/partner of the household head, from the Dutch Time Use Survey, 2000 and 2005. *Commuting* is the time devoted to “travel to or from work” and is measured in hours per day. *Diff. Men-Women* measures the difference in the overall value of the variable for men and women, *P-value diff* shows the *P*-value of a *t*-type test of equality of *means.*

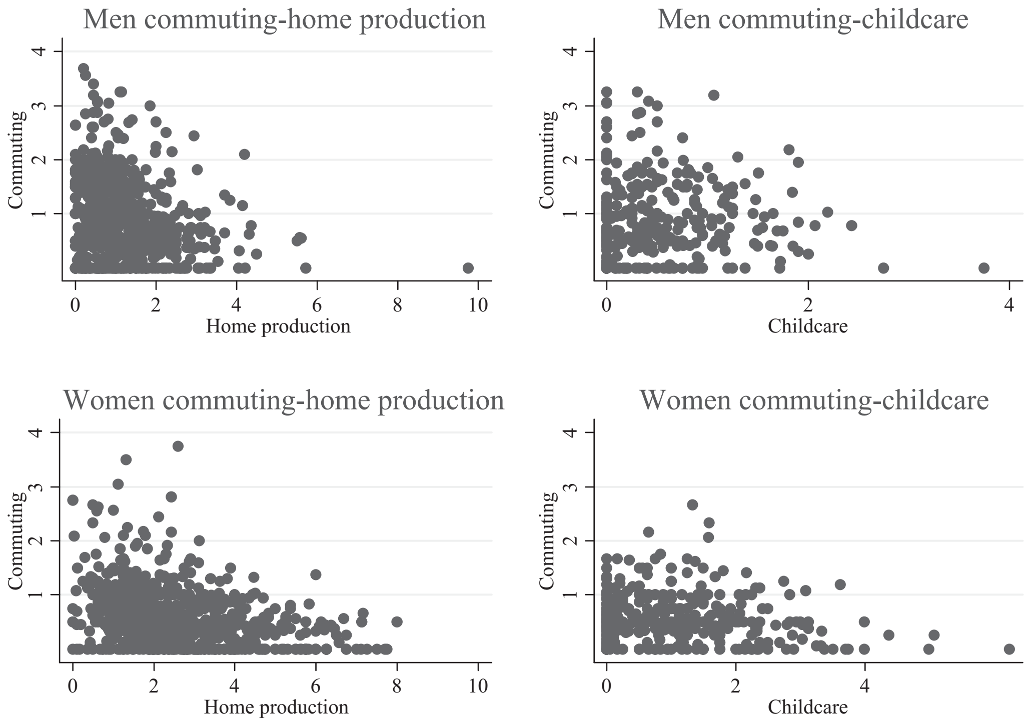


Notes: Sample consists of married male and female respondents aged 21–65, who are the head of the household or the spouse/partner of the household head, from the Dutch Time Use Survey, 2000 and 2005. *Commuting* is the time devoted to "travel to or from work." *Home Production* includes the time devoted to "food preparation, cooking," "set table, wash/put away dishes," "cleaning," "laundry, ironing, clothing repair," "home/vehicle maintenance/improvement," "other domestic work," "purchase goods," "consume other services," "pet care (other than walk dog)," "adult care," "child/adult care-related travel," and ""travel for shopping, personal or household care." *Childcare* includes the time devoted to "physical, medical childcare," "teach, help with homework," "read to, talk or play with child," and "supervise, accompany, other childcare." Time use activities are measured in hours per day. The analysis is restricted to working days, defined as those with more than 60 minutes of market work, excluding commuting.

FIGURE 2: K-Density Functions for Commuting Time, Home Production, and Childcare.

Figure 2 shows kernel-density distributions for the time devoted to *Commuting*, *Home Production*, and *Childcare*, for both men and women.[8] We observe that the time devoted to *Commuting* is concentrated between 0 and 2 hours per day for both men and women, and that the variation in *Commuting* for women is smaller than the variation for men, as the variance coefficients yield values of 0.70 for men and 0.32 for women. Considering the time devoted to *Home Production* by men and women, we observe that it is concentrated in less than four hours per day for males, and six hours per day for females, yielding variance coefficients of 4.42 for men and 5.87 for women, showing that there is more daily variation in *Home Production* time for females than for males. For the time devoted to *Childcare* by men and women who have at least one child under 18, we observe that it is

[8]The analysis is restricted to working days, defined as days when respondents devote 60 or more minutes to market work activities, excluding commuting, with market work defined as the sum of the time devoted to the categories main7 "paid work, main job (not at home)," main8 "paid work at home," main9 "second or other job not at home," main11 "travel as part of work," and main12 "other time at workplace."

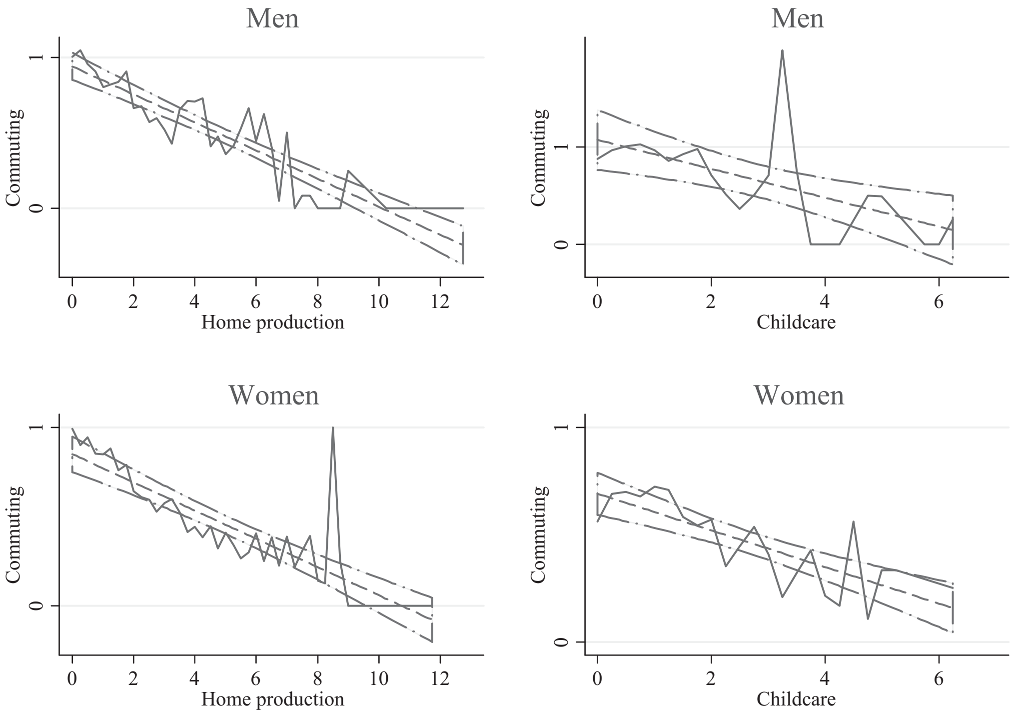


Notes: Sample consists of married male and female respondents aged 21–65, who are the head of the household or the spouse/partner of the household head, from the Dutch Time Use Survey, 2000 and 2005. *Commuting* is the time devoted to “travel to or from work.” *Home Production* includes the time devoted to “food preparation, cooking,” “set table, wash/put away dishes,” “cleaning,” “laundry, ironing, clothing repair,” “home/vehicle maintenance/improvement,” “other domestic work,” “purchase goods,” “consume other services,” “pet care (other than walk dog),” “adult care,” “child/adult care-related travel,” and “travel for shopping, personal or household care.” *Childcare* includes the time devoted to “physical, medical childcare,” “teach, help with homework,” “read to, talk or play with child,” and “supervise, accompany, other childcare.” Time use activities are measured in hours per day. The analysis is restricted to working days, defined as those with more than 60 minutes of market work, excluding commuting.

FIGURE 3: Mean Time Devoted by Individuals to Commuting, Home Production, and Childcare.

concentrated in less than two hours per day, and there is more daily variation in the time devoted to this activity for women, as variance coefficients for men and women are 0.75 and 2.04, respectively. We also note that the time devoted to these three activities does not follow a normal distribution, as the values of skewness and kurtosis are different for reference values of 0 and 3, respectively.

Figure 3 plots the mean time devoted to *Commuting*, on the one hand, and the time devoted to *Home Production* and *Childcare*, on the other, at the individual level, for both men and women, on working days. Specifically, for a given individual and for the days that the individual reported positive time in market work (days when individuals devote at least one hour to market work, excluding commuting), we compute the average time devoted to these activities, obtaining values for *Commuting*, *Home Production*, and *Childcare* for the reference individual. We then plot (scatterplot) the mean time devoted to *Commuting* (y-axis) on the time devoted to *Home Production* or *Childcare* (x-axis) for all individuals. In the case of men, we observe that, in the range between zero and two hours



Notes: Sample consists of married male and female respondents aged 21–65, who are the head of the household or the spouse/partner of the household head, from the Dutch Time Use Survey, 2000 and 2005. *Commuting* is the time devoted to "travel to or from work." *Home Production* includes the time devoted to "food preparation, cooking," "set table, wash/put away dishes," "cleaning," "laundry, ironing, clothing repair," "home/vehicle maintenance/improvement," "other domestic work," "purchase goods," "consume other services," "pet care (other than walk dog)," "adult care," "child/adult care-related travel," and "travel for shopping, personal or household care." *Childcare* includes the time devoted to "physical, medical childcare," "teach, help with homework," "read to, talk or play with child," and "supervise, accompany, other childcare." Time use activities are measured in hours per day. The analysis is restricted to working days, defined as those with more than 60 minutes of market work, excluding commuting.

FIGURE 4: Mean Time Devoted to Commuting, by Mean Time Devoted to Home Production and Childcare.

of *Commuting*, where most observations are concentrated, the variation is rather small. In the case of women, we observe a larger variation in the distribution, as the points are more evenly distributed over the different times devoted to *Home Production* and *Childcare*. Thus, it appears that there is a greater variation for women in the relationship between *Commuting*, and *Home Production* and *Childcare*.

Figure 4 plots the average time devoted to *Commuting* for each time devoted to *Home Production* and *Childcare*; that is, for all the diaries with the same amount of time devoted to *Home Production*, we average the time devoted to *Commuting* by gender. The same applies to *Childcare* time. We plot mean *Commuting* time (y-axis) on the time devoted to *Home Production* or *Childcare* (x-axis). We have also added a linear prediction of *Commuting* time on *Home Production* or *Childcare*, including confidence intervals at the 95 percent level. As can be seen, the linear predictions are a good fit for both men and women, as many values of *Commuting* are in the confidence intervals of the linear prediction. Additionally, the linear prediction yields a negative slope for the relationship between *Commuting* and *Home Production* and *Childcare*, indicating that there is a negative raw correlation between *Commuting* and the other two nonmarket work activities. Raw partial correlations show that the correlation between *Commuting* and *Home Production* is −0.30 and −0.32 for men and women, while the correlation between *Commuting* and *Childcare* is −0.10 and −0.13 for men and women, respectively.

4. EMPIRICAL STRATEGY

We estimate ordinary least squared (OLS) regressions on the time devoted to commuting. However, since some individuals report no time in commuting during their days (24.86 percent and 27.91 percent of men and women, respectively, during their working days) there can be some controversy regarding the selection of alternative models, such as that of Tobin (1958). According to Frazis and Stewart (2012), OLS models are preferred in the analysis of time allocation decisions, since estimation techniques for limited dependent variables that assume a nonlinear functional form, such as the Tobit model, will be inconsistent if we want to estimate means of long-run time use from a sample of daily observations. Gershuny (2012) argues that estimations derived from single-day diaries have the problem of too many zeros, but traditional diary studies can still produce accurate estimates of mean times in activities for samples and subgroups. Within this framework, Foster and Kalenkoski (2013) compare the use of Tobit and OLS models in the analysis of the time devoted to childcare activities, and find that the qualitative conclusions are similar for the two estimation methods. Thus, we rely on OLS models, although we have alternatively estimated Tobit models, and our qualitative conclusions are the same.

The statistical model is as follows. For a given individual "*I*," let C_{ij} represent the daily hours individual "*i*" on day "*j*" devotes to commuting, let $Home\_Production_{ij}\,/\,Childcare_{ij}$ be the time devoted to home production/childcare by individual "*i*" in day "*j*," let X_i be a vector of sociodemographic and regional characteristics, and let ε_{ij} be random variables that represent unmeasured factors. We estimate the following equations:[9]

$$C_{ij} = \alpha + \beta_1 Home\_Production_{ij} + \gamma X_i + \varepsilon_{ij}, \tag{1}$$

$$C_{ij} = \alpha + \beta_2 Home\_Production_{ij} + \beta_3 Childcare_{ij} + \gamma X_i + \varepsilon_{ij}, \tag{2}$$

where $Commuting_{ij}$ represents the time devoted to *Commuting* by individual "*i*" on day "*j*" ($j = 1, 3 \ldots 7$), and $Home\_Production_{ij}$ and $Childcare_{ij}$ is the time devoted to *Home Production and Childcare* by individual "*i*" on day "*j*." Given that we expect childless individuals to devote no time to *Childcare*, we estimate different equations for childless individuals and individuals with children. Additionally, for individuals with children there may be a trade-off between the time devoted to *Home Production* and *Childcare* (e.g., mothers may invest more time in *Childcare* and reduce their time in *Home Production*) and therefore the time devoted to *Commuting*, *Home Production*, and *Childcare* should be jointly determined. Thus, Equation (1) is estimated using only the sample of childless individuals and Equation (2) is estimated using the sample of individuals with children.

Where the raw data show a negative relationship between *Commuting*, and *Home Production* and *Childcare* (see Figure 4), we would expect to find that $\beta_1 < 0$, $\beta_2 < 0$, and $\beta_3 < 0$. Given prior research showing that the factors affecting time-allocation decisions

[9]We have estimated our models using an alternative definition of childcare and home production. In this case, childcare includes the time devoted to the category "child/adult care-related travel." For the case of home production, for those individuals without children we can assume that this "child/adult care-related travel" category refers to adult care time, and thus for childless individuals we include this category as home production. Results are consistent to those reported here, and are available upon request.

of men and women are different (Gimenez-Nadal and Sevilla, 2011, 2012; Gimenez-Nadal and Molina, 2013), we run each model separately by gender. As the distributions of *Commuting*, *Home Production*, and *Childcare* do not follow a normal distribution, we have corrected the standard errors, and we have additionally clustered the observations at the individual level in order to account for the unobserved heterogeneity of individuals.

The vector X_i includes sociodemographic and regional characteristics, according to the factors reviewed in Section 2.[10] We include age and its square, university education, secondary education, working full-time (as opposed to part-time), whether the partner is employed (a proxy for the commuting probability of the partner), the number of children under 18 in the household, whether the youngest child in the household is under five, between five and 12, or between 13 and 17, if there is at least one motorized vehicle at home (as an indicator of car availability), and whether there is at least one computer at home, to control for the possibility that the respondent may be doing tele-work. We also include a vector of dummy variables to scale the day of the week (Ref.: Saturday), and we cluster observations by individuals to take into account potential variations of commuting times across days.

Existing research has shown a relationship between wages and individual commuting behavior (Van Ommeren, van den Berg, and Gorter, 2000; Rupert, Stancanelli, and Wasmer, 2009), but, unfortunately, the DTUS does not include wages or earnings of individuals. However, to the extent that income and education have been found to have a positive relationship to commuting time, we use education and household income as proxies for earnings. This household income refers to monthly household income in €. Moreover, prior research has shown a relationship between occupation and commuting (Hanson and Johnston, 1985; Gordon, Kumar, and Richardson, 1989; Hanson and Pratt, 1995), as female-dominated occupations are more evenly distributed compared to men, and thus women may choose jobs closer to home. One of the limitations of the DTUS is that contains no information on occupation, despite that we can control for whether the individual works in the public sector or not, since the category of female-dominated occupations includes jobs in the public sector (Sandow and Westin, 2010). Thus, we cannot identify the relationship between commuting time and nonmarket work (home production and childcare) net of individual heterogeneity in occupations. We expect that this heterogeneity in occupations may induce an upward bias in the relationship between gender, commuting, and nonmarket work, as one channel that may explain gender differentials in commuting behavior is a gender-segregated labor market, despite the fact that Sandow and Westin (2010) find that women consistently have shorter commutes than men employed in the same sector.

Finally, we include a set of variables that may be considered relevant from the point of view of land use/geographical factors, and considering the aggregation level that we are able to obtain with the two data sets. The first refers to the urban/rural residence of individuals, as we do have information on whether individuals live in an urban or rural area. This variable is originally coded by the MTUS team and so we cannot vary the definition of urban/rural residence. Additionally, there is information on the region of residence of the respondent, coded according to the 12 major regions in the Netherlands (Drenthe, Flevoland, Friesland, Gelderland en Zop, Groningen, Limburg, Noord Brabant, Noord Holland, Overijssel en Nop, Utrecht, Zeeland, and South Holland) plus an additional variable including respondents in Amsterdam, Rotterdam, and The Hague. With this information, we include dummy variables to control for the regional residence of respondents, with South Holland being the reference category. We have included the

[10]Table 1 shows summary statistics for all the sociodemographic and land use/geographical variables.

population density and housing prices defined for these regions. To compute the population density, we obtained figures from EUROSTAT for each of the 12 regions in both 2000 and 2005, and for the category with the three cities we have considered the population density for Amsterdam. In the case of housing prices, for each region, we have used the average purchase price (in thousands) of all dwellings, obtained from the Statistics Netherlands, and for the category with the three cities we have considered the average purchase price in Amsterdam.[11]

Propensity Score Matching

We must be aware of endogeneity in our analysis, since commuting distance, commuting time, and nonmarket work activities could all be related to unobserved factors that influence the individual choices of where to live, where to work, and how to get from one to the other. Thus, to estimate the empirical relationship between commuting and nonmarket work hours, we must deal with potential endogeneity between commuting and the time devoted to home production or childcare as they are jointly determined at the individual level.

The problem we face here is familiar to analysts of the relationship between wages and the uses of time. The effect of wages on market and nonmarket work activity can be endogenous because a given individual may accept a lower wage as a compensating differential for greater flexibility and autonomy in time use. Furthermore, more time spent in housework may reduce the accumulation of human capital, and thus reduce the individual wage. Confronted with this potential endogeneity, many studies have used "predicted" or "imputed" wages as instruments for real wages. For instance, Kimmel and Connelly (2007) use a predicted wage derived from a standard two-step Heckman correction in their analysis of the uses of time of men and women in the U.S. Kalenkoski, Ribar, and Stratton (2009) use predicted wages to examine the impacts of own and partner wages on parents' provision of child care and market work on weekdays, and on weekends and holidays. Gimenez-Nadal and Molina (2013) use predicted wages in their analysis of the time devoted to childcare in Spain and the U.K.

Thus, we need a method to obtain "predicted" or "imputed" time use variables (*Home Production* and *Childcare*), and we propose the use of Propensity Score Matching (PSM). The PSM method was originated by Rosenbaum and Rubin (1983) to evaluate employment and education programs (Lalonde, 1986; Fraker and Maynard, 1987; Heckman, Ichimura, and Todd, 1997; Dehejia and Wahba, 1999, 2002), for use when an experimental design is not feasible, or when the evaluation questions are broader than simply assessing the effect of an intervention on participants. The interest in PSM accelerated after Heckman et al. (1998) assessed the validity of its use to characterize selection bias using experimental data. Dehejia and Wahba (2002) and Caliendo and Kopeinig (2008) describe the technique in great detail. To the best of our knowledge, only Connelly and Kimmel (2009), Borra, Sevilla, and Gershuny (2013), and Gimenez-Nadal and Molina (2014) have used PSM to obtain imputed values of time use.

The PSM propensity score matching essentially estimates each individual's propensity to receive a binary treatment (via a probit or logit) as a function of observables, and

[11] We have additionally included a set of variables to measure the infrastructure of the region (i.e., the stock of total vehicles (in thousands), the number of deaths in road accidents, and the total number of passengers embarked and disembarked (in thousands)) and conditions of the labor markets (unemployment rates). All these variables must be measured at the regional level, and thus we rely on data from EUROSTAT, where they are disaggregated at the regional level that we have in our data (NUTS2). The inclusion of these variables does not change our main conclusions, and results are available upon request.

matches individuals with similar propensities. The technique employs a predicted probability of group membership (treatment vs. control group), based on observed predictors usually obtained from a probit regression, to create a counterfactual group. In our case, the treatment (being selected for the STUS 2005) is completely random, given that the households surveyed are randomly chosen from the population census. We use this method to replace the original *Home Production* and *Childcare* data from any respondent, with actual data from another respondent, that is, every respondent is matched on observable characteristics with a similar respondent, and the time use information of the latter is assigned to the former. In this way, we maintain the original commuting of individuals, but we have "imputed" times for *Home Production* and *Childcare*.

We could, alternatively, have used a linear prediction of uses of time. However, several advantages can be utilized by comparing PSM over regression, including (1) the variation in the imputed variables (*Home Production and Childcare*) that occurs in the donor diary is maintained so far as possible (Connelly and Kimmel, 2009); (2) it restricts the analysis to samples for which there is overlap in covariate distributions across data sets (Dehejia and Wahba, 2002); and (3) it does not impose functional form restrictions on the distribution of covariates (Zhao, 2008). The advantage of PSM compared to other matching methods is that it develops a single (propensity) score that encapsulates multiple characteristics, rather than requiring a one-to-one match of each characteristic, simplifying matching by reducing dimensionality.

To implement propensity score matching, both data sets are combined and a dummy variable is constructed taking value 1 if the observation belongs to the DTUS 2005, and value 0 if the observation belongs to the DTUS 2000. The propensity score is defined as the probability of belonging to the DTUS 2005, conditional on the common observed covariates ($p(X_i) = \Pr(i \in \mathit{DTUS\ 2005} \mid X = x)$). Hence, we consider individuals included in the 2005 survey as if they are the treated group, and individuals included in the 2000 survey as if they are the untreated group. Thus, individuals from 2000 are used to impute the time devoted to nonmarket work (home production and childcare) by individuals in 2005, and individuals from 2005 are used to impute the time devoted to nonmarket work by individuals in 2000. This imputed nonmarket work time can still be used to examine the relationship between commuting time and nonmarket work hours, since the imputed variable preserves the variation of the original data. Additionally, given that the same factors may differentially affect the time devoted to both home production and child care, depending on the gender of the respondents, we apply this matching strategy by gender.

We first specify and estimate a binomial probit model of the probability of belonging to the 2005 sample; that is, we obtain the propensity score. Second, we impose the common support condition; that is, we restrict the 2000 sample to observations whose estimated propensity scores lie within the ranges of estimated propensity scores of the 2005 sample (we lose one male observation from the 2000 sample). Third, we pair each individual from the DTUS 2005 with another individual from the DTUS 2000 using the nearest-neighbor criterion with sample replacement (Connelly and Kimmel, 2009). The nearest-neighbor criterion links each observation in the DTUS 2000 to the observation with the closest propensity score in the DTUS 2005. We used a one-to-one match with replacement, such that one observation can be linked to more than one other observation. We impute the time devoted to *Home Production* and *Childcare* for observations in both the DTUS 2000 and 2005. In this final step, we impute the uses of time for observations in the DTUS 2005 using information from their neighbors in the DTUS 2000, and vice versa, so that observations in both 2000 and 2005 have imputed values of individuals from the other survey. During this matching process, each diary is considered as an independent observation, since for each individual we treat each of the seven diary days as if they were independent observations.

TABLE 2: Propensity Score Coefficients Estimates

Propensity Scores Estimates	(1) Men	(2) Women
Living in urban area	0.272***	0.326***
	(0.046)	(0.045)
Education	0.100***	0.286***
	(0.024)	(0.025)
Time in personal care	0.031***	.0178**
	(0.010)	(0.009)
Time in Market work	0.029***	0.031***
	(0.009)	(0.009)
At least one computer at home	0.714***	0.972***
	(0.059)	(0.052)
Working day	0.006	0.291***
	(0.080)	(0.066)
Constant	−1.432***	−2.326***
	(0.143)	(0.130)
Observations	5,291	6,327
Pseudo R^2	0.041	0.112

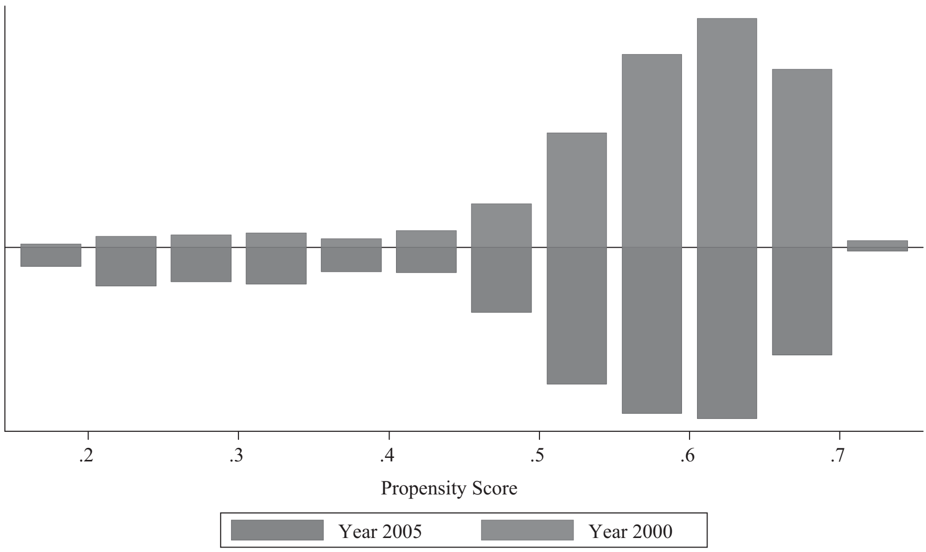
Notes: Sample consists of male and female respondents aged 21–65, who are the head of the household or the spouse/partner of the household head, from the Dutch Time Use Survey, 2000 and 2005. *Personal care* and *market work* are measured in hours per day. *Significant at the 90 percent level; **significant at the 95 percent level; ***significant at the 99 percent level.

Table 2 shows the results from the probit model of the likelihood of belonging to the 2005 sample, for men and women separately. We run a probit regression of the binary indicator, taking value "1" for observations in the 2005 sample and "0" for observations in the 2000 sample, over the set of common variables. We consider the demographic and personal characteristics of the respondents (education), household characteristics (living in urban area, computer at home), and time-use behavior (time devoted to personal care and market work, diary was collected during a working day). In the estimation of the propensity score, the balancing property is fulfilled (the mean propensity score is the same for treated and untreated individuals in each block).[12] Figures 5 and B show the propensity score histograms for both data sets, and for men and women, respectively, showing a high degree of overlap between the two distributions, indicating that the common support assumption is satisfied.

5. RESULTS

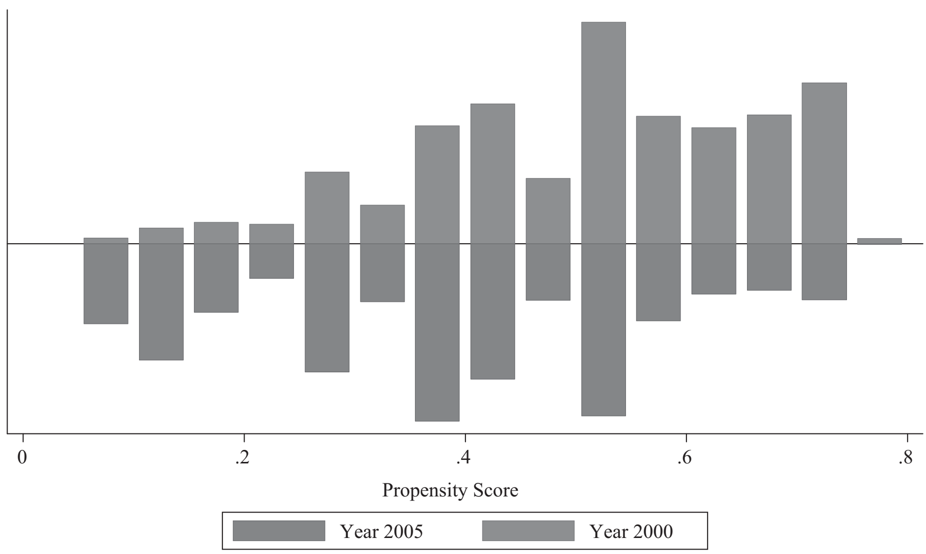
Columns (1) and (2) in Table 3 show the results of estimating Equation (1) on the time devoted to *Commuting* for men and women when *Home Production* is considered in

[12]In the literature of evaluation of public policies/programs, researchers must face the dimensionality problem, which is the lack of common support between treated and untreated groups with cells containing treated observations and/or untreated observations only, and it arises when the number of covariates is large, or many of the covariates have many values, or are continuous. In this framework, the "Balancing Property" establishes that the mean propensity score must not be different for treated and untreated individuals in each cell, and if this property is not fulfilled, a less parsimonious specification of the propensity score is needed. The fulfillment of this property prevents us from choosing all the covariates used as controls in our main regressions, and only a limited set of such covariates can be included as covariates in the PSM.



Notes: Sample consists of married male respondents aged 21–65, who are the head of the household or the spouse/partner of the household head, from the Dutch Time Use Survey, 2000 and 2005. Individuals in the year 2005 are considered the treated group, and individuals in the year 2000 are considered the untreated group.

FIGURE 5: Distribution of the Estimated Propensity Score for Years 2000 and 2005, Men.



Notes: Sample consists of married female respondents aged 21–65, who are the head of the household or the spouse/partner of the household head, from the Dutch Time Use Survey, 2000 and 2005. Individuals in the year 2005 are considered the treated group, and individuals in the year 2000 are considered the untreated group.

FIGURE 6: Distribution of the Estimated Propensity Score for Years 2000 and 2005, Women.

childless individuals. Columns (3) and (4) in Table 3 show the results of estimating Equation (2) on the time devoted to *Commuting* for men and women when *Home Production* and *Childcare* are considered in individuals with children. According to the results using the original time use variables, for childless individuals, we find that *Home Production* is negatively related to the time devoted to *Commuting*, consistent with results obtained from Figure 3. One additional hour of *Home Production* per day is associated with 0.086 and 0.073 fewer hours of *Commuting* per day for both men and women, respectively. In the case of individuals with children one additional hour of *Home Production* is associated with 0.080 and 0.073 fewer hours of *Commuting* per day, while one additional hour of *Childcare* per day is associated with 0.095 and 0.070 fewer hours of *Commuting* per day, for men and women, respectively. These results imply that as the time devoted to nonmarket work activities increases, the time devoted to commuting decreases, consistent with the HRH.

If we consider the time devoted to *Home Production* and *Childcare* by the different groups of individuals, we observe that the relatively more time devoted to these activities by women may result in their lower *Commuting* time, compared to their male counterparts. In the case of childless individuals, men and women devote 1.82 and 3.07 average hours per day to *Home Production*, which may suppose 0.156 and 0.224 fewer hours (9.36 and 13.44 fewer minutes) devoted to *Commuting* by both men and women. In the case of individuals with children under 18 in the household, we find that men and women devote on average 1.84 and 4.09 hours per day to *Home Production*, and 0.70 and 1.48 hours to *Childcare*, which may suppose 0.214 and 0.402 fewer hours (12.84 and 24.12 fewer minutes) devoted to *Commuting* by both men and women, respectively. Thus, we observe that household (*Home Production* and *Childcare*) responsibilities are negatively associated with the time devoted to *Commuting* by individuals, with this effect being especially large for women with children under 18. In the specific case of individuals with children, the more time devoted to *Home Production* and *Childcare* by women is associated with a decrease in *Commuting* that is almost double that of men.

However, results for Equations (1) and (2) may be biased, as the time devoted to *Commuting*, *Home Production*, and *Childcare* are jointly determined, and thus our results may suffer from endogeneity between commuting time and nonmarket work activities. Columns (5) to (8) in Table 3 show the results of estimating Equations (1) and (2) on the time devoted to *Commuting*, where the time devoted to *Home Production* and *Childcare* have been imputed using Propensity Score Matching to take into account reverse causality issues.[13] These results can be interpreted as being free of the problem of reverse causality, despite that we cannot identify the relationship between commuting time and labor market hours net of individual unobserved heterogeneity.

Columns (5) and (6) show a negative relationship between *Commuting* and *Home Production* for childless men and women, with both coefficients being statistically significant at standard levels. We find that one hour of *Home Production* is associated with a decrease of 0.017 hours per day of *Commuting* for men, while for women it is associated with a decrease of 0.039 hours of *Commuting* per day. Thus, the negative relationship between commuting time and time devoted to home production is more significant for women, by a factor close to two. A *t*-type test of equality of the coefficients indicates that the coefficients differ ($P < 0.01$), indicating that the effect of *Home Production* on *Commuting* is greater for women than for men. Considering the HRH, we interpret this result

[13] Given that we are using generated regressors in regressions shown in Columns (5) to (8), we follow Pagan (1984), Murphy and Topel (1985), and Gimenez-Nadal and Molina (2013) and bootstrap the standard errors of such regressions. In doing so, we have replicated 1,000 each regression where 1,000 replications where a random sample with replacement is drawn from the total number of observations.

TABLE 3: Results for Commuting, Home production, and Childcare

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS Models with Original Time				*OLS Models with Imputed Time*			
	Childless Individuals		*Individuals with Children*		*Childless Individuals*		*Individuals with Children*	
Dep. var: Commuting Time	Men	Women	Men	Women	Men	Women	Men	Women
Home Production	−0.086***	−0.073***	−0.080***	−0.073***	−0.017***	−0.039***	−0.012	−0.037***
	(0.007)	(0.005)	(0.008)	(0.005)	(0.006)	(0.004)	(0.013)	(0.003)
Childcare	–	–	−0.095***	−0.070***	–	–	−0.006	−0.024***
	–	–	(0.020)	(0.008)	–	–	(0.023)	(0.006)
Demographic characteristics								
Age	0.012	0.020*	0.063	−0.011	0.008	0.015	0.055	−0.003
	(0.016)	(0.011)	(0.042)	(0.018)	(0.016)	(0.011)	(0.047)	(0.018)
Age squared	−0.014	−0.024**	−0.079	0.015	−0.010	−0.020	−0.070	0.006
	(0.019)	(0.012)	(0.048)	(0.024)	(0.019)	(0.012)	(0.054)	(0.024)
Secondary education	−0.043	0.030	0.011	0.020	−0.038	0.038	0.004	0.022
	(0.060)	(0.034)	(0.089)	(0.036)	(0.066)	(0.034)	(0.100)	(0.040)
University education	0.082	0.097**	0.175*	0.061	0.080	0.101**	0.148	0.044
	(0.067)	(0.047)	(0.094)	(0.039)	(0.072)	(0.050)	(0.102)	(0.040)
Working full-time	0.250***	0.253***	0.267***	0.127**	0.298***	0.289***	0.422***	0.196***
	(0.056)	(0.041)	(0.080)	(0.064)	(0.062)	(0.044)	(0.093)	(0.066)
Partner employed	0.104**	−0.049	0.057	0.008	0.102**	−0.057	0.043	0.000
	(0.047)	(0.036)	(0.065)	(0.047)	(0.049)	(0.039)	(0.069)	(0.057)
Number of children <18	–	–	−0.069**	0.010	–	–	−0.102***	−0.034
	–	–	(0.035)	(0.017)	–	–	(0.036)	(0.021)
Youngest child <5	–	–	0.218	0.112*	–	–	0.125	0.019
	–	–	(0.141)	(0.060)	–	–	(0.144)	(0.058)
Youngest child 5–12	–	–	0.111	0.128***	–	–	0.096	0.065
	–	–	(0.103)	(0.048)	–	–	(0.107)	(0.048)
At least one motorized vehicle at home	0.038	−0.041	−0.012	0.022	0.018	−0.036	0.043	0.053
	(0.060)	(0.048)	(0.129)	(0.037)	(0.062)	(0.049)	(0.163)	(0.044)
At least one computer at home	−0.011	0.011	0.016	0.025	0.003	0.000	−0.016	0.014
	(0.064)	(0.036)	(0.133)	(0.048)	(0.069)	(0.039)	(0.150)	(0.049)
Household income	0.001	0.001	0.000	0.001***	0.001	0.001	0.001	0.001

(*Continued*)

TABLE 3: Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS Models with Original Time				*OLS Models with Imputed Time*			
	Childless Individuals		*Individuals with Children*		*Childless Individuals*		*Individuals with Children*	
Dep. var: Commuting Time	Men	Women	Men	Women	Men	Women	Men	Women
	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)	(0.002)	(0.003)	(0.001)
Public sector	0.040	0.013	−0.101	−0.003	0.024	0.020	−0.115	0.018
	(0.061)	(0.055)	(0.072)	(0.043)	(0.063)	(0.054)	(0.081)	(0.044)
Living in urban area	0.033	−0.014	0.030	0.040	0.055	−0.014	−0.004	0.038
	(0.060)	(0.045)	(0.072)	(0.031)	(0.068)	(0.047)	(0.077)	(0.035)
Population density	0.003	0.000	0.004	0.000	0.003	0.000	0.005	0.000
	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)	(0.003)	(0.005)	(0.002)
Housing prices	−0.246	0.165	−0.179	0.126	−0.227	0.145	−0.204	0.147
	(0.158)	(0.109)	(0.241)	(0.094)	(0.167)	(0.131)	(0.284)	(0.121)
Amsterdam, Rotterdam, and the Hague	−10.403	0.318	−14.488	−0.223	−10.882	0.095	−17.021	−0.413
	(10.934)	(8.182)	(14.330)	(6.999)	(12.101)	(8.196)	(15.975)	(7.770)
Drenthe	3.141	−0.090	4.379	0.038	3.252	−0.034	5.178	0.081
	(3.435)	(2.541)	(4.483)	(2.186)	(3.810)	(2.546)	(5.004)	(2.431)
Flevoland	3.308	−0.102	3.912	0.089	3.502	−0.020	4.607	0.143
	(3.190)	(2.399)	(4.211)	(2.051)	(3.547)	(2.400)	(4.685)	(2.283)
Friesland	3.150	0.014	4.110	0.060	3.347	0.119	4.939	0.064
	(3.363)	(2.489)	(4.411)	(2.150)	(3.730)	(2.493)	(4.918)	(2.392)
Gelderland en Zop	2.731	−0.109	3.490	0.144	2.870	−0.015	4.103	0.139
	(2.773)	(2.048)	(3.642)	(1.760)	(3.072)	(2.053)	(4.065)	(1.963)
Groningen	3.114	0.065	3.883	0.129	3.276	0.130	4.572	0.139
	(3.177)	(2.356)	(4.156)	(2.011)	(3.526)	(2.361)	(4.631)	(2.241)
Limburg	2.001	0.162	2.891	0.020	2.157	0.160	3.404	−0.018
	(2.263)	(1.689)	(2.972)	(1.447)	(2.509)	(1.691)	(3.317)	(1.613)
Noord Brabant	2.464	−0.071	3.175	−0.019	2.558	−0.004	3.766	−0.018
	(2.455)	(1.812)	(3.237)	(1.563)	(2.725)	(1.816)	(3.616)	(1.745)
Noord Holland	0.930	0.035	1.052	0.007	0.948	0.082	1.210	−0.031
	(0.867)	(0.631)	(1.144)	(0.544)	(0.961)	(0.634)	(1.282)	(0.610)

(*Continued*)

TABLE 3: Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS Models with Original Time				*OLS Models with Imputed Time*			
	Childless Individuals		*Individuals with Children*		*Childless Individuals*		*Individuals with Children*	
Dep. var: Commuting Time	Men	Women	Men	Women	Men	Women	Men	Women
Overijssel en Nop	2.646	−0.060	3.921	0.020	2.771	0.000	4.603	0.104
	(2.934)	(2.173)	(3.852)	(1.867)	(3.254)	(2.172)	(4.296)	(2.079)
Utrecht	1.342	−0.093	1.937	0.045	1.387	−0.051	2.240	0.013
	(1.331)	(0.961)	(1.735)	(0.843)	(1.471)	(0.963)	(1.939)	(0.941)
Zeeland	3.133	−0.051	4.171	0.136	3.320	−0.012	4.890	0.077
	(3.324)	(2.451)	(4.380)	(2.136)	(3.682)	(2.454)	(4.886)	(2.377)
Constant	−3.813	−0.541	−6.278	0.005	−4.116	−0.523	−7.210	−0.295
	(3.865)	(2.842)	(5.128)	(2.488)	(4.266)	(2.842)	(5.730)	(2.750)
Observations	2,949	3,466	2,253	2,721	2,949	3,466	2,253	2,721
Pseudo R^2	0.254	0.286	0.249	0.250	0.209	0.247	0.207	0.161

Notes: Robust standard errors clustered at the individual level in parentheses for columns (1)–(4). Bootstrap standard errors accounting for the use of generated regressors are reported in parentheses for columns (5)–(8). Sample consists of male and female respondents aged 21–65, who are the head of the household or the spouse/partner of the household head, from the Dutch Time Use Survey, 2000 and 2005. *Commuting* is the time devoted to "travel to or from work." *Home Production* includes the time devoted to "food preparation, cooking," "set table, wash/put away dishes," "cleaning," "laundry, ironing, clothing repair," "home/vehicle maintenance/improvement," "other domestic work," "purchase goods," "consume other services," "pet care (other than walk dog)," "adult care," "child/adult care-related travel," and ""travel for shopping, personal or household care." *Childcare* includes the time devoted to "physical, medical childcare," "teach, help with homework," "read to, talk or play with child," and "supervise, accompany, other childcare." Time use activities are measured in hours per day. *Significant at the 90 percent level; **significant at the 95 percent level; ***significant at the 99 percent level.

as that these responsibilities impose more restrictions on commuting time for women than for men, which would explain why women have shorter commutes.

Furthermore, if we look at the relationship between *Commuting*, *Home Production*, and *Childcare* for men and women with children, we find that only *Home Production* and *Childcare* of women have negative and statistically significant relationships with the time devoted to *Commuting*, as one hour of *Home Production* and *Childcare* for women is related to a decrease of 0.037 and 0.024 hours, respectively, in the *Commuting* time of women. In the case of men, we find no statistically significant relationship between *Commuting*, and *Home Production* and *Childcare*. When we control for the potential endogeneity of Commuting on *Home Production* and *Childcare*, we find that only *Home Production* and *Childcare* by women reduces commuting time, while we find no effect for men. This result is consistent with the HRH.

It is a truism that there are social roles in society, and those roles vary by gender, with our results in this work providing a specific example: women adapt their commuting patterns to their chores (home production and childcare), leading them to take jobs closer to home and thus reducing their commuting time and distance (Turner and Neimeier, 1997; Sandow and Westin, 2010).

Regarding the rest of the sociodemographic and geographic/land use factors, we find that working full-time, as opposed to part-time, is positively related to commuting time (McQuaid and Chen, 2012), which is related to higher wage rates of these types of worker (Madden, 1981; Van Ommeren and Dargay, 2006). Also, in the case of male workers, a larger number of children is associated with less time commuting, although the age of the children does not appear to be a relevant factor.

6. CONCLUSIONS

The existing literature has shown that commuting entails monetary as well as mental/physical health costs, and many urban and job search models have included commuting as one of the variables of interest, although the evidence of gender differentials in commuting behavior has been inconclusive. In this paper, we analyze time use data from three developed countries to determine whether there are gender-variant differences in commuting duration, and whether any such differences have held relatively constant over time. One theory proposed to explain shorter commutes by women is the HRH, which posits that the disproportionate burden of household responsibility on women necessitates shorter commuting times and makes it more difficult for them to work away from home.

In this paper, we analyze the relationship between commuting time and the time devoted to both home production and childcare, with a focus on gender differentials. In doing so, we use a sample of working individuals from the DTUS of 2000 and 2005 to empirically address the relationship between commuting time and the time devoted to both home production and childcare activities. In our empirical analysis, we take into account that the time devoted to commuting, home production, and childcare are choices workers make, and we thus propose the use of a matching strategy (Propensity Score Matching) to deal with the potential reverse causality between commuting time and household responsibilities. Our results show that the effect of home production on commuting time for women is more than double the effect for men, while childcare time affects only women's commuting time; this is consistent with the HRH.

We hope that our results will stimulate further research on the topic of commuting behavior and its connection to household responsibilities. Theoretical, as well as further empirical, research is needed to shed light on the question of how gender affects individual commuting behavior. Furthermore, employment policies should consider the relationship between commuting and household responsibilities, as more family-friendly policies would increase the desire of women to work farther from home, which could ultimately increase their labor force participation.

An extension of the analysis shown in this paper could focus on how the mode of transport is affected by individual household responsibilities. It could be that women may be more likely than men to use public transportation due to their household responsibilities, or that they have a lower priority to use the car in the household. On the contrary, women with greater household responsibilities could be more dependent on a car due to their tight time budget and complex trip-chaining. In the specific case of the Netherlands, and considering the data sets used throughout this paper, women in their commuting trips have a lower propensity to use private modes of transport, such as cars or motorbikes, while they are more likely to commute by walking, cycling, or using other physically active transport. In the case of public transport, the difference between men and women is relatively small. Despite that we are analyzing time devoted to commuting, and not the commuting distance, the fact that women are more likely to use physically active transport, together with shorter commuting times, may indicate that women also have shorter commuting distance, which may be important for housing, market work, and transportation policies. We leave this issue for further research.

The data used in this paper impose two limitations. First, it is a cross-section of individuals, which does not allow us to identify the relationship between commuting and household production hours net of (permanent) individual heterogeneity in preferences. Second, our data do not include information on wages or occupations, and so we cannot ascertain the relationship between commuting and household production hours, net of individual heterogeneity, in wages and occupations (factors that have been shown to affect individual commuting behavior and the gender gap). Alternative data sets with a panel data structure, such as the British Household Panel Survey and the Panel Study of Income Dynamics, both of which provide information on market-work hours, and which lend themselves to a similar matching strategy, could be used to investigate this topic. We leave this issue for future research.

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