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Commuting Time and Labour Supply in the Netherlands

A Time Use Study

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Abstract

We examine whether commuting time has any effect on worker labour supply, using the Dutch Time Use Surveys of 2000 and 2005. Our results show an inverted U-shaped relationship between commuting time and labour market supply of men and women, with a maximum reached at 3.22 hours of commuting per day. We use Propensity Score Matching to deal with potential endogeneity between labour supply and commuting time. Our results indicate that commuting is positively related to work duration within certain time-space constraints, but later, physical capability constraints come into play.

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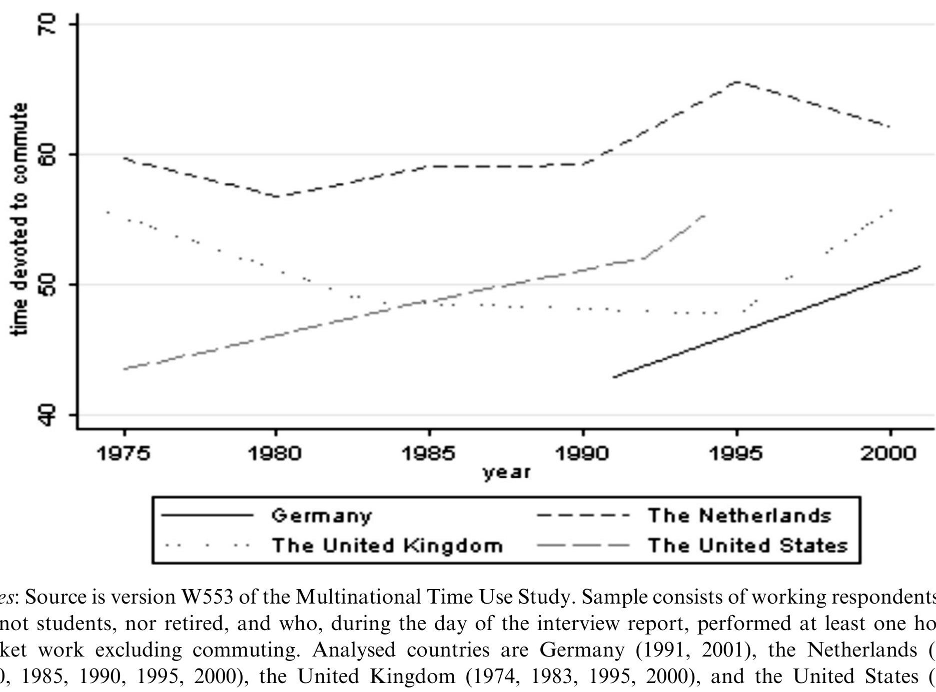
1.0 Introduction

This paper analyses the relationship between workers' commute and labour market hours, using the Propensity Score Matching (PSM) technique to deal with potential endogeneity between labour supply and commuting time. As shown in Figure 1, the overall commuting time of workers in many developed countries has increased in recent decades. In particular, daily commuting times increased in Germany by eight minutes between 1991 and 2001, by three minutes in the Netherlands between 1975 and 2000, and by twelve minutes in the United States between 1975 and 1994. This evidence is consistent with existing studies. Susilo and Maat (2007) show that commuting time increased in the Netherlands between 1993 and 2005, and Kirby and LeSage (2009) find an increase in average commuting times in the USA between 1990 and 2000. These increases, and the fact that commuting time represents a significant part of the total time devoted to the labour market (Kenworthy and Laube, 1999), make the analysis of the consequences of commuting time an interesting topic of research, given its monetary and mental/physical health costs (Koslowsky *et al.*, 1995; Stutzer and Frey, 2008; Roberts *et al.*, 2011).

Despite the importance of commuting time in individual decisions, as shown by its inclusion in urban-economic spatial models of firm and household location (Muth,

Figure 1
Trends in Commuting Time, 1970s–2000s



Notes: Source is version W553 of the Multinational Time Use Study. Sample consists of working respondents who are not students, nor retired, and who, during the day of the interview report, performed at least one hour of market work excluding commuting. Analysed countries are Germany (1991, 2001), the Netherlands (1975, 1980, 1985, 1990, 1995, 2000), the United Kingdom (1974, 1983, 1995, 2000), and the United States (1975, 1985, 1992, 1994). Time devoted to commuting is computed as the total time devoted to the variable *av5* 'time to/from work'.

1969), or job search models (Rupert *et al.*, 2009), there is little evidence of the effect of commuting on labour supply. To the best of our knowledge, only two papers have directly analysed the relationship between commuting time and hours of work. Using travel-time ratios for the Netherlands, Schwanen and Dijst (2002) find a positive association between commute length and hours worked, within certain time-space constraints, and then find a negative association as physical capability constraints come into play. Gutiérrez-i-Puigarnau and van Ommeren (2010) find for a sample of German workers that commuting distance slightly increases daily and weekly labour supply, and that the number of workdays is not affected. Evidence of the relationship between commuting time and labour market hours is scarce and inconclusive, and more research on this topic is needed.

We use the sample of working individuals from the Dutch Time Use Surveys (DTUS) of 2000 and 2005 to empirically address the relationship between commuting time and market work hours. One substantial advantage 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 across days. In our empirical analysis, we take into account that commuting and labour market hours are choices that workers make, and we thus propose the use of a matching strategy (Propensity Score Matching) to deal with potential endogeneity between labour supply and commuting time.

We find an inverted U-shaped effect of commuting on labour market hours, with a maximum commute of 3.22 hours for both men and women, beyond which time the relationship turns negative. These results are consistent with Schwanen and Dijst (2002), using travel-time ratios for the Netherlands, who find that between four and eight hours of work, commuting time rises monotonically, while with more than eight hours, commuting time tends to decrease with work duration. Our results indicate that commuting time is positively related to work duration within certain time-space constraints, and that these constraints become more binding, and physical capability constraints come into play (Hägerstrand, 1970), when extensive commuting is required after a long workday. We also find that the relationship between commuting time and labour market hours is positive up to six and four hours of work for men and women, respectively, and then the relationship turns negative. Furthermore, the effect of a one-unit change in commute time for male and female workers, with an average commute time (0.58 and 0.31 hours per day, respectively), is around 0.45 hours for both men and women.

The remainder of the paper is organised as follows. Section 2 describes the data used in the paper, Section 3 describes the empirical strategy, Section 4 presents the main results, and Section 5 sets out our main conclusions.

2.0 Data: The Dutch Time Use Survey 2000 and 2005

The data used for the empirical analysis is drawn from the versions of the Dutch Time Use Survey 2000 and 2005, included in the Multinational Time Use Study (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 twelve or older, was selected to report information on daily activities during seven consecutive days. The diary time-frame is twenty-four consecutive hours (from 12 : 00 a.m. until 12 : 00 a.m. the following day) and is divided into fifteen-minute intervals.

Our variables of interest refer to the daily time devoted to market work and commuting. To compute the variable *Market work*, we use the time use information gathered in the variables *main7* 'paid work, main job (not at home)', *main8* 'paid work at home', *main9* 'second or other job not at home', *main11* 'travel as a part of work', and *main12* 'other time at workplace'. We sum the time reported in these five categories to obtain the time devoted to *Market work* during the day.[1] For the variable *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. We have information for both *Market work* and *Commuting* at the individual level for the seven days of the week.

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 twenty-one and sixty-five (inclusive). Our results can thus be interpreted as being 'per working adult'. We carry out the analysis by gender, given existing evidence that the time use patterns of men and women are different (Aguiar and Hurst, 2007; Guryan *et al*., 2008; Gimenez-Nadal and Sevilla, 2012; Gimenez-Nadal and Molina, 2013). In this context, Pazy *et al*. (1996), Turner and Niemeier (1997), and Plaut (2006) all report that men have longer commutes than women, probably due to the fact that women work closer to home because they are more active in home production (Turner and Niemeier, 1997).

2.1 Empirical evidence

Table 1 shows the mean time devoted to *Market work* and *Commuting* for individuals in our sample, by gender. We observe that men devote 5 and 0.6 hours per day to *Market work* and *Commuting*, respectively, while women devote 2.6 and 0.3 hours per day to those activities. We thus find a gender difference in the time devoted to *Commuting*, with male workers devoting more time to this activity compared to their female counterparts, consistent with the existing literature showing that men have longer commutes than women (Pazy *et al*., 1996; Turner and Niemeier, 1997; Plaut, 2006). Additionally, if we construct the travel-time ratio ($\tau = T_c / T_c + T_{MW}$), as in Schwanen and Dijst (2002), where τ is the travel-time ratio, and T_c and T_{MW} are the times devoted to *Commuting* and *Market work*, respectively, we find that the mean travel-ratio in our sample is 10.33 per cent for males and 10.87 per cent for females, consistent with the findings of Schwanen and Dijst (2002). This shows that workers in the Netherlands spend on commuting, on average, 10.5 per cent of the time available for working and travelling.

[1] We have used an alternative definition of market work that excludes the time devoted to market work at home, since paid work at home and paid work not at home could respond differently to such things as traffic congestion. Our results are consistent to the exclusion of market work at home as part of market work activities (results available upon request). Given the general interest the paper has in the relationship between commuting time and labour supply, we focus on the more general definition of market work that includes paid work at home.

Table 1
Summary Statistics

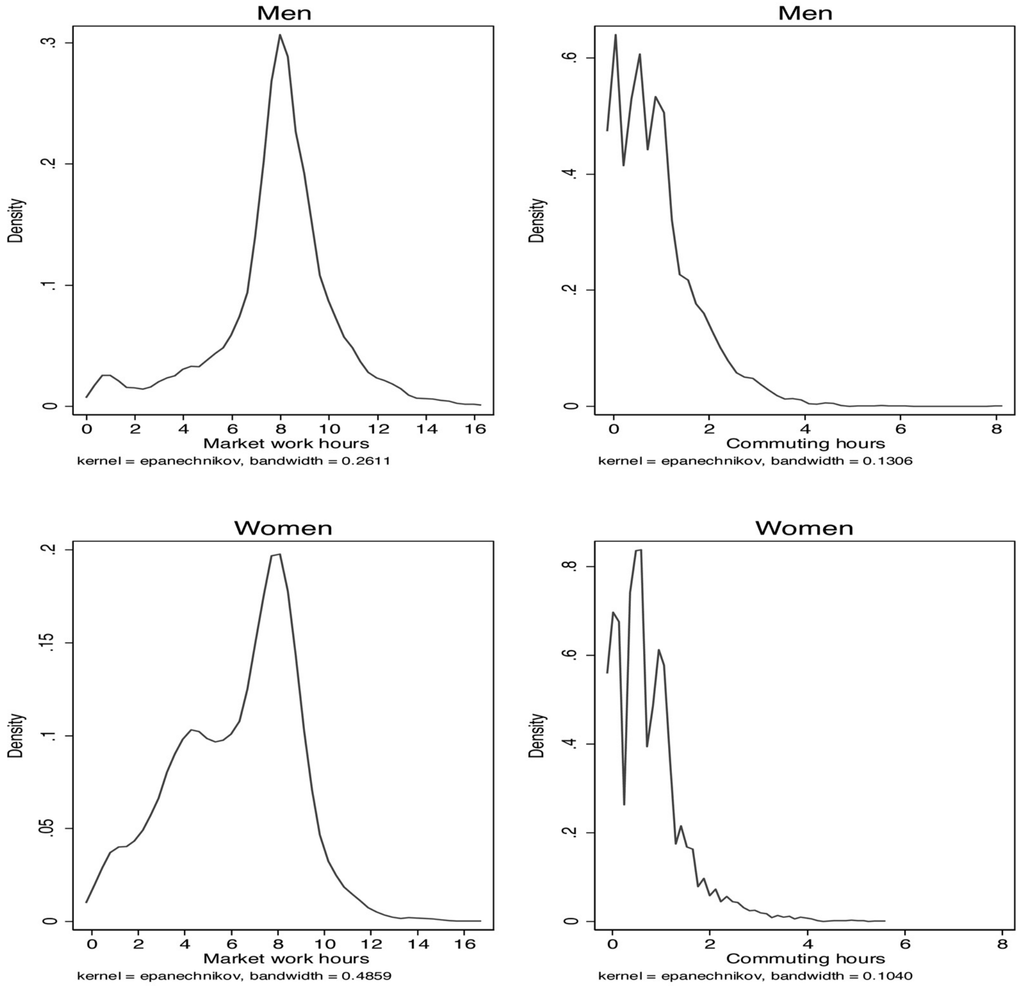
	Males		*Females*	
	Mean	*SD*	*Mean*	*SD*
Time use variables				
Market work	5.005	(0.058)	2.569	(0.044)
Commuting	0.577	(0.011)	0.313	(0.008)
Socio-demographic variables				
Age	41.923	(0.140)	40.626	(0.139)
University education	0.342	(0.007)	0.460	(0.006)
Secondary education	0.473	(0.007)	0.383	(0.006)
Working full-time	0.951	(0.003)	0.428	(0.007)
Living in a couple	0.775	(0.006)	0.736	(0.006)
Partner employed	0.528	(0.007)	0.674	(0.006)
Living in urban area	0.824	(0.005)	0.833	(0.005)
Ln(household income)	4.617	(0.044)	5.178	(0.042)
Number of children <18	0.843	(0.015)	0.776	(0.013)
Youngest child 0–4	0.177	(0.005)	0.187	(0.005)
Youngest child 5–13	0.185	(0.005)	0.168	(0.005)
Number of family members	2.893	(0.020)	2.741	(0.016)
Public sector	0.149	(0.005)	0.154	(0.005)
Head of the household	0.906	(0.004)	0.315	(0.006)
At least one computer at home	0.886	(0.004)	0.837	(0.005)
At least one motorised vehicle at home	0.905	(0.004)	0.854	(0.004)
No vehicle at home	0.089	(0.004)	0.133	(0.004)
Observations	5,216	6,190		

Notes: Standard deviations in parenthesis. Sample consists of respondents aged twenty-one to sixty-five, from the Dutch Time Use Survey 2000 and 2005, available in the Multinational Time Use Study. *Market work* includes the time devoted to 'paid work–main job (not at home)', 'paid work at home', 'second or other job not at home', 'travel as a part of work', and 'other time at workplace'. *Commuting* includes the time devoted to 'travel to or from work'. *Market work* and *Commuting* are measured in hours per day.

Figure 2 shows kernel-density distributions for the time devoted to *Market work* and *Commuting* for both men and women, restricting the analysis to days where individuals devote positive time to *Market work* (working days). We observe that the time devoted to *Market work* is concentrated around eight hours per day for both men and women, but the distribution of *Market work* for women has two peaks, one at four hours per day, and another at eight hours per week. This may be due to gender differences in the proportion of full-/part-time workers. While 95.1 per cent of males in our sample work full-time, only 42.8 per cent of females in our sample work full-time (see Table 1). The Coefficient of Variation (CV) for males is 0.79, while the CV for females is 1.13, indicating that there is more daily variation in the time devoted to *Market work* by females.

Considering the time devoted to *Commuting* by both men and women, we observe that it is concentrated for times lower than two hours per day, yielding skewness values

Figure 2
K-density Functions for Market Work and Commuting

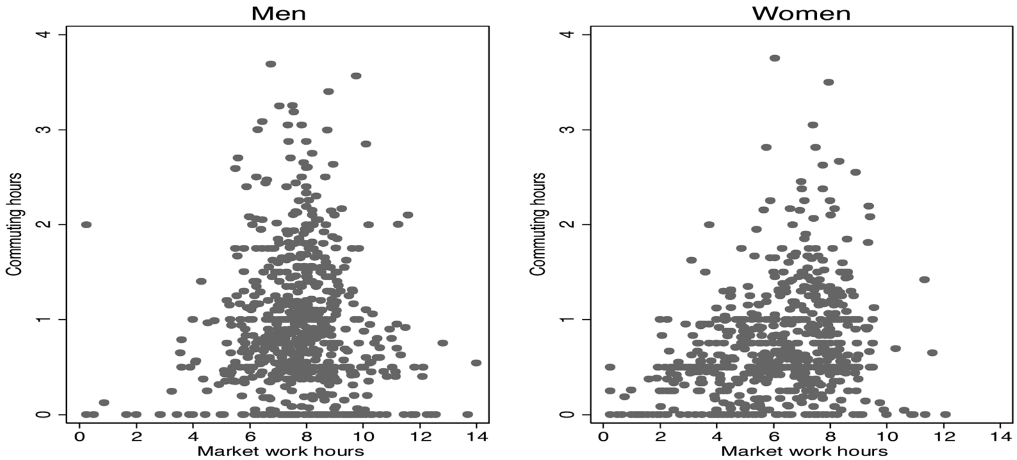


Notes: Sample consists of male and female respondents aged twenty-one to sixty-five, from the Dutch Time Use Survey 2000 and 2005. *Market work* includes the time devoted to 'paid work–main job (not at home)', 'paid work at home', 'second or other job not at home', 'travel as a part of work', and 'other time at workplace'. *Commuting* includes the time devoted to 'travel to or from work'. *Market work* and *Commuting* are measured

of 2.17 and 2.86, respectively. Thus, this time does not follow a normal distribution, for neither males nor females, and we also note that there is more daily variation in this time for males than for females, as the CVs are 0.67 and 0.43, respectively.

Figure 3 plots the mean time devoted to *Market work* and *Commuting* at the individual level, for both men and women, on working days. In particular, for a given individual and for the days that the individual reported positive time in *Market work*,

Figure 3
Mean Time Devoted by Individuals to Market Work and Commuting

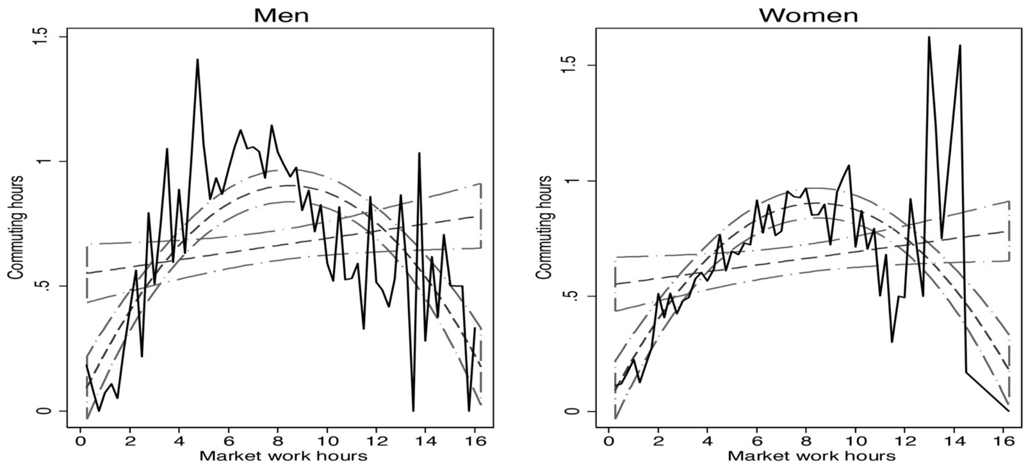


Notes: Sample consists of respondents aged twenty-one to sixty-five, from the Dutch Time Use Survey 2000 and 2005. *Market work* includes the time devoted to 'paid work–main job (not at home)', 'paid work at home', 'second or other job not at home', 'travel as a part of work', and 'other time at workplace'. *Commuting* includes the time devoted to 'travel to or from work'. *Market work* and *Commuting* are measured in hours per day. Scatter plots show the mean time devoted to *Market work* and *Commuting* for each individual of the sample (averaged over the seven days of the week).

we compute the average time devoted to these two activities, obtaining one value for *Market work* and *Commuting* for the reference individual. We then plot (scatter plot) the mean time devoted to *Commuting* (y-axis) on the time devoted to *Market work* (x-axis) for all individuals. In the case of men, we observe that in the range between six and ten hours, 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 *Market work*. This is probably due to the large proportion of women working part-time, since many of them devote only four hours per day to market work activities. Thus, it seems that there is a larger variation for women in the relationship between *Commuting* and *Market work*.

Finally, Figure 4 plots the average time devoted to *Commuting* for each time devoted to *Market work* — that is, for all the diaries with the same amount of time devoted to *Market work*, we average the time devoted to *Commuting* by gender. For instance, for all male diaries with eight hours of *Market work*, we average the time devoted to *Commuting* and we obtain a mean value of *Commuting* of 1.04 hours. We plot mean *Commuting* time (y-axis) on the time devoted to *Market work* (x-axis). We have also added a linear and quadratic prediction of *Commuting* time on *Market work*, including confidence intervals at the 95 per cent level. As can be seen, the quadratic predictions are a better fit, compared to the linear predictions, for both men and women, as many more values of *Commuting* are in the confidence intervals of the quadratic prediction compared to the linear prediction.

Figure 4
Mean Time Devoted to Commuting, by Mean Time Devoted to Market Work



Notes: Sample consists of respondents aged twenty-one to sixty-five, from the Dutch Time Use Survey 2000 and 2005. *Market work* includes the time devoted to 'paid work–main job (not at home)', 'paid work at home', 'second or other job not at home', 'travel as a part of work', and 'other time at workplace'. *Commuting* includes the time devoted to 'travel to or from work'. *Market work* and *Commuting* are measured in hours per day. Line plots show the mean time devoted to *Commuting* for each mean time devoted to *Market work*. Linear and quadratic fit have been added.

3.0 Empirical Strategy

We estimate ordinary least squared (OLS) regressions on the time devoted to *Market work*, by gender. However, since we observe a high proportion of 'zeros' for *Market work* (for example, on 40 per cent of the days, individuals reported no time devoted to the labour market), 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, and Gershuny (2012) argues that traditional diary studies can still produce accurate estimates of mean times in activities for samples and subgroups. Foster and Kalenkoski (2013) compare the use of tobit and OLS models in the analysis of the time devoted to childcare activities, finding that the qualitative conclusions are similar for the two estimation methods.

We estimate the following equation by OLS regressions:

$$MW_i = \alpha + \beta_1 Commuting_i + \beta_2 Commuting\_Squared_i + \varepsilon_i, \quad (1)$$

where MW_i represents the time devoted to *Market work* by individual '*i*', and $Commuting_i$ and $Commuting\_Squared_i$ is the time devoted to *Commuting* by individual '*i*' and its square, respectively. This model will serve to inquire into the relationship between market work and commuting time. Where the raw data shows an inverted U-shaped relationship between *Market work* and *Commuting* (see Figure 4), we would expect to find that $\beta_1 > 0$ and $\beta_2 < 0$.

However, in the previous model, we do not take into account the observed heterogeneity of individuals that may lead to differences in commuting time, such as age or the presence of children. Thus, we estimate the following regression:

$$MW_i = \alpha + \beta_1 Commuting_i + \beta_2 Commuting\_Squared_i + \gamma X_i + \eta Day_i + \varepsilon_i, \qquad (2)$$

where the vector X_i includes standard individual and household characteristics (Gimenez-Nadal *et al.*, 2010, 2012; Gimenez-Nadal and Ortega, 2010) such as age and its square, university education, secondary education, number of children aged under eighteen in the household, working in the public sector, and whether the respondent is, or is not, the head of the household.[2] 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.

Prior research has shown a relationship between wages and individual commuting behaviour (van Ommeren *et al.*, 2000; Rupert *et al.*, 2009). Unfortunately, the DTUS does not include wages or earnings of individuals, and the best we can do is to use household income (log) as a proxy for individual wages. Prior research has also shown a relationship between occupation and commuting (Hanson and Johnston, 1985; Gordon *et al.*, 1989; Hanson and Pratt, 1995), but there is no information on the occupation of individuals, and we can control only whether or not the respondent works in the public sector. Thus, we cannot identify the relationship between commuting time and labour market hours net of individual heterogeneity in wages and occupations.

3.1 Propensity Score Matching

We must beware of endogeneity in our analysis, since commuting distance, commuting time, and working hours 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 labour market hours, we must deal with potential endogeneity between labour supply and commuting time. As a method to overcome this problem, we propose the use of Propensity Score Matching (PSM) to impute the time devoted to commuting. Our strategy is based on Borra *et al.* (2013), where the authors use a statistical matching method to combine data from two different data sets to obtain imputed values of several uses of time.

The PSM method was originally proposed by Rosenbaum and Rubin (1983) aimed at the evaluation of employment and education programmes (Lalonde, 1986; Fraker and Maynard, 1987; Dehejia and Wahba, 2002), and it is suitable when an experimental design is infeasible, or when the evaluation questions are broader than assessing the effect of an intervention on participants. It also allows us to match individuals in a treatment group to others who did not participate, but have comparable characteristics.

The innovation 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. The interest in PSM accelerated after Heckman *et al.* (1998a,b) assessed the validity of using propensity matching to characterise selection bias using experimental data. PSM employs a predicted probability of group membership (treatment vs. control

[2]Table 1 shows means and standard deviations of the explanatory variables.

group), based on observed predictors usually obtained from a logistic regression to create a counterfactual group.

One of the advantages of these matching methods over regression is that the variation in the imputed variable that occurs in the donor data set is simulated as closely as possible, given that a unique donor value can be found for each recipient record (Connelly and Kimmel, 2009). Another benefit is that it restricts inferences to samples for which there is overlap in covariate distributions across data sets (the common support region), thereby avoiding unwarranted model extrapolations (Dehejia and Wahba, 2002). A further advantage of matching over regression analysis is that it is non-parametric: matching does not impose functional form restrictions such as linearity and homogeneous effects on the distribution of covariates, both assumptions being usually unjustified, either by the economic theory or by the data (Zhao, 2008). Moreover, matching does not require exclusion restrictions for the identification of the imputed variable when used in the combined data set.

To implement propensity score methods, both data sets are combined and a dummy variable is constructed, taking value 1 if the observation belongs to the recipient file DTUS 2005, and value 0 if the observation belongs to the donor file DTUS 2000. The propensity score is defined as the probability of belonging to the recipient database, conditional on the common observed covariates ($p(X_i) = \Pr(i \in \text{DTUS 2005} \mid X = x)$). 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. We use individuals from 2000 to impute the time devoted to commuting by individuals in 2005, and individuals from 2005 to impute the time devoted to commuting by individuals in 2000. This imputed commuting time can still be used to examine the relationship between commuting time and labour market hours, since the imputed variable preserves the variation of the original data.

Our matching strategy is implemented as follows. 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 recipient unit with that donor for which the difference between the propensity score is lower in absolute values, and impute the time devoted to commuting for the individual. In this last step, we consider 2005 as recipients and 2000 as donors, and also 2000 as recipients and 2005 as donors, so that individuals 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 shows the results from the probit model of the likelihood of belonging to the 2005 sample. 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 (university education, partner employed), household characteristics (living in urban area, computer at home), and time use behaviour (time devoted to personal care, time devoted to housework, diary was collected during the weekend). In the

Table 2
Propensity Score Coefficients Estimates

Propensity scores estimates	*(1)*
University education	0.126*** (0.026)
Living in urban area	0.378*** (0.033)
Personal care	0.011 (0.007)
Housework	−0.017** (0.007)
Computer at home	0.806*** (0.042)
Partner employed	0.067** (0.027)
Weekend	−0.004 (0.030)
Constant	−0.969*** (0.085)
Observations	10,198
Pseudo R-squared	0.046

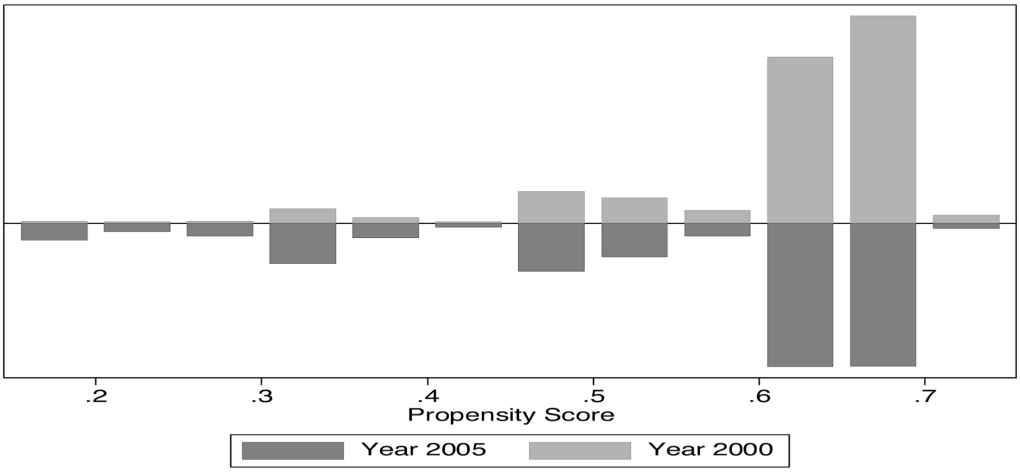
Notes: Robust standard errors in parenthesis, clustered by individuals. Sample consists of respondents aged twenty-one to sixty-five, from the Dutch Time Use Survey 2000 and 2005, available in the Multinational Time Use Study. *Personal care* and *Housework* are measured in hours per day.
*Significant at the 90 per cent level; **Significant at the 95 per cent level; ***Significant at the 99 per cent level.

estimation of the propensity score, nine blocks are created and the balancing property is fulfilled (the mean propensity score is not different for treated and untreated individuals in each block).[3] Figure 5 shows the propensity score histograms for both data sets, showing a high degree of overlap between the two distributions, indicating that the common support assumption is satisfied.

Finally, the distribution of the imputed variable is compared to the distribution of the original variable to see whether there are significant differences. Table 3 shows the descriptive statistics of original and imputed *Commuting* for the two surveys. For the year 2000, the original time devoted to commuting is 0.502 with standard deviation of

[3]In the literature of evaluation of public policies/programmes, researchers must face the dimensionality problem, which consists of the lack of common support between the treated and untreated groups with cells containing treated observations and/or untreated observations only. 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 fulfilment of this property prevents us from choosing all the covariates used as controls in our main regressions.

Figure 5
Distribution of the Estimated Propensity Score for Years 2000 and 2005



Notes: Sample consists of respondents aged twenty-one to sixty-five, 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.

0.750, while the imputed time devoted to commuting is 0.485 with standard deviation of 0.715. A *t*-test of differences in means between the two variables shows that we can accept that the means of the two variables are equal, with a *p*-value of 0.29. For the year 2005, the original time devoted to commuting is 0.497 with standard deviation of 0.749, while the imputed time devoted to commuting is 0.523 with standard deviation of 0.753. A *t*-type test of differences in means between the two variables shows that we cannot reject that the means of the two variables are equal, with a *p*-value of 0.06. Thus, we can assume that, after our matching strategy, imputed time devoted to commuting yields similar values to the original time devoted to commuting.

Table 3
Descriptive Statistics of Original and Estimated Variables

	N Obs.	*Mean*	*SD*	*Min*	*Max*	*Proportion zero commuting*	*Correlation with working hours*
					Year 2000		
Original commuting	4,185	0.502	0.750	0	9.75	49.22	0.559
Matching commuting	4,185	0.485	0.715	0	8.25	46.45	0.131
					Year 2005		
Original commuting	6,012	0.497	0.749	0	8.25	45.94	0.459
Matching commuting	6,011	0.523	0.753	0	9	50.43	0.097

Notes: Sample consists of respondents aged twenty-one to sixty-five, from the Dutch Time Use Survey 2000 and 2005. *Commuting* includes the time devoted to the following category 'travel to or from work', and is measured in hours per day.

Once we have checked that our matching strategy is consistent, we estimate the following regression:

$$MW_i = \alpha + \beta_1 \overline{Commuting_i} + \beta_2 \overline{Commuting\_Squared_i} + \gamma X_i + \eta Day_i + \varepsilon_i, \quad (3)$$

where $\overline{Commuting_i}$ and $\overline{Commuting\_Squared_i}$ represent the imputed time devoted to *Commuting* by individual '*i*' and its square, respectively.

4.0 Results

Table 4 shows the results of estimating equations (1), (2), and (3) for males (columns 1, 2, and 3) and females (columns 4, 5, and 6). In columns (1) and (4), where we estimate equation (1) for men and women, we observe an inverted U-shaped raw relationship between *Commuting* and the time devoted to *Market work*, consistent with the raw relationship observed in Figure 5. We find that the relationship between *Commuting* and *Market work* is positive up to 2.92 and 2.79 hours per day for males and females, respectively, after which it turns negative. In columns (2) and (5), we estimate equation (2) for both males and females, and we observe that results for the relationship between *Commuting* and *Market work* are consistent to the inclusion of individual observed heterogeneity. In particular, we find an inverted U-shaped relationship between *Commuting* and the time devoted to *Market work*, with a maximum reached at 2.73 and 2.70 hours of *Commuting* for men and women, respectively.

Columns (2) and (4) show an inverted U-shaped relationship between *Commuting* and *Market work*, with the maximum reached at 2.73 and 2.70 hours of *Commuting* per day for men and women, respectively, corresponding to 7.5 and 8 hours per day of *Market work*, respectively. These results indicate that the relationship between *Market work* and *Commuting* is positive up to eight hours of work, after which the relationship turns negative as commuting time decreases with the time devoted to market work. Our results are consistent with Schwanen and Dijst (2002), who find that from four to eight hours of work, commuting time rises monotonically, while from eight or more hours, commuting time tends to decrease with work duration, indicating that it is positively related to work duration within certain time-space constraints, although these constraints become more binding, and physical capability constraints come into play, with extensive commuting after a long workday.

However, results for equations (1) and (2) may be biased, as the time devoted to *Commuting* and *Market work* are jointly determined, and thus our results may suffer from potential endogeneity between labour supply and commuting time. Columns (3) and (6) show results of estimating equation (3) for both men and women, respectively, where we use the imputed time devoted to *Commuting* from our Propensity Score Matching strategy. As can be observed, we still obtain an inverted U-shaped relationship between *Commuting* and *Market work*, but the coefficients are much smaller than in equations (1) and (2), which may indicate that prior results were biased. When we use the imputed time devoted to commuting, we obtain an inverted U-shaped relationship between *Commuting* and *Market work*, with a peak at 3.22 hours of commuting, after which the relationship turns negative. Our results differ from Schwanen and Dijst (2002), as the relationship between *Market work* and *Commuting* is positive up to a different

Table 4
Results for Market Work and Commuting

Results for market work hours	*(1)*	*(2)* Males	*(3)*	*(4)*	*(5)* Females	*(6)*
	OLS model with no controls	*OLS model with controls*	*OLS model with PSM*	*OLS model with no controls*	*OLS model with controls*	*OLS model with PSM*
Commute	4.468^{***} (0.380)	2.375^{***} (0.278)	0.477^{***} (0.115)	6.001^{***} (0.377)	4.904^{***} (0.344)	0.471^{***} (0.106)
Commute squared	-0.764^{***} (0.156)	-0.434^{***} (0.094)	-0.074^{**} (0.036)	-1.077^{***} (0.180)	-0.907^{***} (0.150)	-0.073^{**} (0.032)
Demographic characteristics						
Age	–	-0.151^{**} (0.066)	-0.119^{*} (0.064)	–	−0.030 (0.051)	−0.028 (0.056)
Age squared	–	0.161^{**} (0.079)	0.116 (0.077)	–	0.011 (0.064)	−0.004 (0.069)
Secondary education	–	0.475^{**} (0.214)	0.447^{**} (0.219)	–	0.100 (0.198)	0.433^{**} (0.204)
University education	–	0.391^{*} (0.211)	0.416^{*} (0.216)	–	0.034 (0.215)	0.610^{***} (0.219)
Working full-time	–	1.120^{***} (0.323)	1.258^{***} (0.349)	–	1.006^{***} (0.160)	1.569^{***} (0.164)
Living in couple	–	−0.159 (0.252)	−0.055 (0.247)	–	0.657^{**} (0.334)	0.650^{*} (0.334)
Partner employed	–	−0.119 (0.185)	−0.138 (0.182)	–	−0.182 (0.305)	−0.495 (0.309)
Living in urban area	–	-0.679^{***} (0.189)	-0.713^{***} (0.185)	–	0.121 (0.136)	0.126 (0.156)
Ln(household income)	–	0.002 (0.103)	0.104 (0.108)	–	−0.009 (0.047)	0.087^{*} (0.049)
Number of children <18	–	0.404^{**} (0.189)	0.254 (0.194)	–	0.111 (0.131)	0.048 (0.147)
Youngest child 0–4	–	−0.038 (0.285)	0.074 (0.286)	–	-0.745^{***} (0.232)	-1.151^{***} (0.244)
Youngest child 5–13	–	−0.253 (0.311)	−0.066 (0.314)	–	-0.363^{*} (0.220)	-0.569^{**} (0.229)

Number of family members	–	−0.209	−0.150	–	0.005	0.117
		(0.129)	(0.130)		(0.095)	(0.116)
Public sector	–	−0.206	−0.209	–	−0.010	0.039
		(0.166)	(0.163)		(0.150)	(0.158)
Head of the household	–	0.101	0.155	–	0.682***	0.694***
		(0.277)	(0.277)		(0.235)	(0.236)
At least one computer at home	–	0.464*	0.496*	–	0.419**	0.522**
		(0.252)	(0.261)		(0.194)	(0.209)
At least one motorised vehicle at home	–	−2.645***	1.553***	–	−0.033	−0.381
		(0.364)	(0.345)		(0.653)	(0.735)
No vehicle at home	–	−3.318***	−2.142***	–	−0.296	−0.584
		(0.418)	(0.409)		(0.660)	(0.751)
Constant	3.349***	6.061***	3.289**	1.466***	0.207	−0.540
	(0.127)	(1.614)	(1.588)	(0.084)	(1.235)	(1.337)
Observations	5,174	5,174	5,173	5,023	5,023	5,023
R-squared	0.283	0.531	0.476	0.455	0.536	0.301

Notes: Robust standard errors in parenthesis, clustered by individuals to allow for differences in the variance/standard errors due to day-to-day individual correlation. Sample consists of respondents aged twenty-one to sixty-five, from the Dutch Time Use Survey 2000 and 2005. *Market work* includes the time devoted to 'paid work–main job (not at home)', 'paid work at home', 'second or other job not at home', 'travel as a part of work', and 'other time at workplace'. *Commuting* includes the time devoted to 'travel to or from work'. *Market work* and *Commuting* are measured in hours per day. Day of the week dummies are included in regressions of Columns (2), (3), (5), and (6).

*Significant at the 90 per cent level; **Significant at the 95 per cent level; ***Significant at the 99 per cent level.

limit, compared to their results. We obtain an inverted U-shaped relationship between *Commuting* and *Market work*, with the maximum reached at 3.22 hours of *Commuting* per day for men and women, corresponding to six and four hours per day of *Market work*, respectively. These results indicate that the relationship between *Market work* and *Commuting* is positive up to six hours of work for men and four hours of work for women, after which the relationship turns negative as commuting time decreases, with the time devoted to market work. Furthermore, the effect of a one-unit change in commute time for male and female workers with an average commute time is around 0.45 hours for men ($0.477 - 0.074 \times 0.577$) and women ($0.471 - 0.073 \times 0.313$).

5.0 Conclusions

The existing literature has shown that commuting entails monetary and mental/physical health costs, and many urban and job search models have included commuting as one of their variables of interest, despite scant evidence on the relationship between commuting and labour market hours. This paper analyses the effect of commuting time on labour supply patterns, using data from the Dutch Time Use Survey for the years 2000 and 2005. Our analysis based on daily market work may be subject to endogeneity problems, and thus we use a matching strategy to impute individual commuting time. We find an inverted U-shaped relationship between commuting and labour market hours, as the maximum effect of commuting on labour market hours is reached at 3.22 hours for men and women, corresponding to six and four hours per day, respectively, devoted to the labour market. These results indicate that the relationship between *Market work* and *Commuting* is positive up to six and four hours of work for men and women, respectively, and then the relationship turns negative as commuting time decreases with the time devoted to market work. Thus, theoretical models should include the possibility that the effects of commuting may be non-linear.

To the best of our knowledge, this is the first paper that directly addresses the relationship between daily market work and commuting, and the evidence presented in this paper may provide a promising line of research for understanding the relationship between commuting time and labour supply. The data used in this paper imposes two limitations. First, our data is a cross-section of individuals, and it does not allow us to identify the relationship between commuting and labour market hours net of (permanent) individual heterogeneity in preferences. Second, our data does not include information on wages or occupation, and thus we cannot ascertain the relationship between commuting and labour market hours net of individual heterogeneity in wages and occupations. Alternative data sets with a panel data structure, such as the British Household Panel Survey, and the Panel Study of Income Dynamics, which have information on market work hours, and where a similar matching strategy to the one developed in this paper can be applied, could be used to investigate this topic. We leave this issue for future research.

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