Commuting Time and Labour Supply: A Causal Effect?*

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Abstract
We analyze the causal effect of the length of the worker's commute on worker's productivity, by examining whether commuting time has any effect on worker's labour market supply. Using the Spanish Time Use Survey 2002-03, our GMM/IV estimation yields a positive causal impact of commuting time on the time devoted to the labour market, with one hour of commuting increasing the time devoted to the labour market by 35 minutes in a working day. Our results shed light on the relationship between commuting and workers behaviour, since daily labour supply should be considered in theoretical models to provide a comprehensive view of commuter behaviour.

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1. INTRODUCTION

There are several reasons why the effect of commuting costs on labour market supply is of interest to economists (for a review, see Gibbons and Machin, 2006). For instance, policy makers may want to know whether congestion, as well as publicly-provided transport infrastructure, affects the decision of individuals with regard to how much time they spend on work (Hymel, 2009). Also, as suggested by Black et al. (2008), it may help to know whether significant increases in female labour supply are due to the reduction in commuting costs, resulting from improvements in transportation technology, or is it only a consequence of the increase of the educational level of women in recent decades. It may also concern employers, as there are many claims that workers with long commuting distances are more often absent and arrive late for work, affecting worker's productivity.

This paper examines the causal effect of commuting time on labour supply patterns, with a focus on daily labour supply defined as the number of hours worked during the day of interview. Many economists consider that higher commuting costs decrease labour supply (e.g. Bovenberg and Goulder, 1996; Mayeres and Proost, 2001; Parry and Bento, 2001), although other models allow for the possibility that commuting time has a positive effect on labour supply (Cogan, 1981; Parry and Bento, 2001; Black et al., 2008). There are divergent theoretical views on how to model the relationship between commuting costs and labour supply, and while some studies assume that the number of workdays is fixed and the number of work hours per day is freely chosen (e.g., Cogan, 1981), other studies make the opposite assumption (e.g., Parry and Bento, 2001).

Prior research done by Gutiérrez-i-Puigarnau and van Ommeren (2010,2011) directly analyses the relationship between commuting distance and labour market behaviour. Gutiérrez-i-Puigarnau and van Ommeren (2010) find that in Germany, distance has a slight positive effect on daily and weekly labour supply, but no effect on the number of workdays, and that the effect is stronger (although still small) for females. Gutiérrez-i-Puigarnau and van Ommeren (2011) find that in Germany, commuting distance induces absenteeism with an elasticity of about 0.07 to 0.09, and thus absenteeism would be 15% to 20% less if all workers had a negligible commute. We complement such previous analysis by analyzing the causal relationship between commuting time and labour market hours. To the best of our knowledge, no other studies have directly analyzed this relationship between commuting time (costs) and labour market behaviour, especially in the field of labour economics.

Using the Spanish Time Use Survey (STUS) 2002-2003, we analyze the causal relationship between commuting time and labour market hours. Cogan (1981) establishes that when fixed costs of employment are present (the main example is commuting), the period of time over which the fixed costs are incurred determines the ideal modelling choice of the period of time of labour supply. That is to say, if fixed costs are per day, such as commuting costs, and these daily costs are important, then the appropriate measure of labour supply is daily labour supply. The STUS is a perfect dataset for this issue, since it allows us to measure the time devoted to both commuting and labour market during the same day, providing information on daily commuting time and on daily market hours. One of the main issues we are concerned with is that commuting time may be endogenous with respect to labour supply (i.e., the longer the commuting time, the shorter the time left for work) and, in consequence, we use GMM/IV models, despite previous literature emphasizing that it is not easy to find valid instruments for commuting distance (e.g., Manning, 2003; Gubits, 2004). We find a positive causal impact of commuting time on the time devoted to the labour market, with one hour of commuting increasing the time devoted to the labour market by 35 minutes in a working day.

By focusing on the relationship between the time devoted to both commuting and labour market hours during a working day, we shed light on how to model the relationship between commuting costs and labour supply. A common assumption in the urban economic literature is that private costs of commuting are fully borne by the worker and do not affect the worker's productivity. However, urban efficiency wage theories allow that worker's work effort is a function of the length of the commute (e.g., Zenou (2002) assumes that workers involuntarily provide less work effort due to larger commutes, while Ross and Zenou (2008) demonstrate that if shirking and leisure time are substitutes in the worker's utility function, then one may expect a positive effect of commuting on shirking). We argue that not only weekly labour supply but also daily labour supply should be considered in theoretical models in order to give a comprehensive view of commuter behaviour.

The remainder of the paper is organized as follows. Section 2 describes the data used in the paper. Section 3 describes the empirical strategy used to overcome the problem of endogeneity between commuting time and labour market hours. Section 4 presents the main results, and Section 5 sets out the main conclusions.

2. DATA: THE SPANISH TIME USE SURVEY 2002-03

The data used for the empirical analysis is drawn from the 2002–3 STUS, part of the Harmonized European Time Use Surveys (HETUS) launched by EUROSTAT, the statistical office of the European Union. It consists of a representative sample of 20,603 households and contains information on daily activities, gathered by means of the completion of a personal diary and household and individual questionnaires. The sample is evenly distributed over the year and the week in order to accurately represent time-use patterns during all days of the week.

The survey includes an activities diary, which all members of the household aged 10 and older complete on a selected day (the same day for all members of the household). An extensive literature confirms the reliability and validity of diary data and their superiority over other time-use surveys based on stylized questions, asking respondents to estimate time spent in activities on a 'typical day' (e.g., Juster and Stafford 1991, Robinson and Godbey 1997). The diaries' time frame is twenty-four consecutive hours (from 6:00 a.m. until 6:00 a.m. the following day) and is divided into ten-minute intervals. In each of the intervals, the respondent records a main activity.

Activities are coded according to a harmonized list established by EUROSTAT and are grouped into ten major categories: personal care, paid work, studies, household and family, volunteer work and meetings, social life and recreation, sports and open-air activities, hobbies and games, means of communication, and non-specified travel and use of time.[1]

Time Use Variables. We consider the time reported to market work/commuting as primary activities in the day of the interview. Thus, *Market Work* is defined as the sum of 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* is defined as the time devoted to "travel to or from work". Both activities are measured in hours per day. What differentiates "travel as a part of work"

[1] A full description of activities can be found in the Spanish Statistical Office, http://www.ine.es/prodyser/micro_emptiem.htm.

from "travel to or from work" is the diarist's perception, in the sense that it is the diarist who codes the activity as being part of work, or as being commuting time. For instance, in cases where the diarist works as a delivery man/woman, it may be the case that he/she needs time to go from home to the place where the delivery van is located (commuting), so that such travelling time is not part of the job.

Sample. For the sake of comparison with previous studies, and to minimize the role of time allocation decisions that have a strong inter-temporal component over the life cycle, such as education and retirement, we restrict our samples to non-retired/non-student individuals between the ages of 24 and 65 (inclusive). Our results can thus be interpreted as being 'per working-age adult' (Aguiar and Hurst 2007). Additionally, we exclude 'low quality' diaries from the analysis, following the Multinational Time Use Study (MTUS) coding procedures.[2]

We also restrict the sample to include only respondents who performed at least one hour of market work during the day of the interview, since there may be cases where respondents are having a day off, but they go to their work place for some non-work purpose. In this situation, we cannot consider such a day as a working day and, for this reason, we consider only individuals who report at least one hour of market work (excluding commuting). Only 1% of the sample who report a positive amount of market work on the diary day indicate working less than one hour. Of this group, 57% report zero time commuting to work. In contrast, only 8% of those reporting at least one hour of market work indicate no commuting time. Those with minimal market work time on the diary day may be doing flexible activities, such as checking email, and can be grouped with those reporting zero time on market work. The final sample consists of 15,798 observations.

Table 1 shows the average time devoted to *Market Work* and *Commuting* by individuals in our sample (Column 1), and the average time devoted to such activities by individuals in our sample who report positive time in *Commuting* (Column 2). We observe that individuals devote 7 hours and 45 minutes to *Market Work* during a working day, and 55 minutes to commuting. The sample correlation between *Market Work* and *Commuting* is 0.13, indicating a significant positive relationship between the

[2] The MTUS team defines any diary having 91 or more minutes of missing time, having fewer than 7 episodes, or missing 2 or more of the four basic activities as a 'low quality' or 'bad case' diary. See http://www.timeuse.org/mtus/guide for more information about how good- and bad-quality diaries are defined.

time devoted to *Market Work* and *Commuting*. Considering individuals who devote positive time to *Commuting*, we find that the time devoted to *Market Work* is 7 hours and 50 minutes per working day, while they devote 1 hour to *Commuting*. 92.70% of the sample report a positive commute. Thus, we do not observe large differences in the time devoted to *Market Work* depending on whether individuals commute during the working day, or not. However, it is difficult to make any causal inferences on the relationship between commuting time and hours in the labour market from these raw figures. The following sections take into account individual observed heterogeneity to shed some light on the causal effect of commuting time on an individual's labour market behaviour.

3. EMPIRICAL STRATEGY

Using *Commuting* as an explanatory variable would produce biased estimates of the time devoted to the labour market, since commuting time is jointly determined with labour market hours. Similarly, we present an Instrumental Variable (IV) linear model in order to deal with endogeneity problems. The 2-equation model can be written as follows:

$$l_i = \alpha_t + \beta_{1t} Commuting_i + \beta_{2t} X_i + \beta_{3t} Z_i + \alpha_t Day_i + \varepsilon_{it} \qquad (1)$$

$$Commuting_i = \alpha_h + \beta_{1h} IV_i + \beta_{2h} X_i + \beta_{3h} Z_i + \alpha_h Day_i + \varepsilon_{ih} \qquad (2)$$

where l_i is the time devoted to the labour market by individual 'i', $Commuting_i$ is the variable indicating the time devoted to commuting by individual 'i', X_i is a vector of personal characteristics, Z_i is a vector of household characteristics, and Day_i is a vector of dummy variables scaling the day of the week (Ref.: Friday). Within this framework, we regress the endogenous variable $Commuting_i$ on a set of excluded instruments (IV_i) and included instruments (X_i, Z_i and Day_i).[3]

The properties of the excluded instruments (IV_i) used in Equation (2) are that they must be correlated with the endogenous explanatory variable ($Commuting_i$), conditional on the other covariates and, secondly, they cannot be correlated with the error term in the explanatory equation (i.e., instruments cannot suffer from the same problem as the original predicting variable). Theoretical urban models essentially assume that residence

[3] See Wooldridge (2002) for more details about IV estimation.

location is endogenous (e.g. Wales, 1978; White, 1988), whereas labour models assume that it is given (e.g. Gubits, 2004; Black et al., 2008). We thus keep residence location constant, and we suppose that residence location decisions are made before or after the current period of analysis, and that such decisions crucially depend on housing prices.

We rely on statistics on housing prices offered by the *Ministry of Public Works* to select the instruments for the analysis. The *Ministry of Public Works* has information (gathered by the *Spanish Statistical Office*) on mean prices of housing at the regional level, measured in €/m^2. We link the regional data offered by the *Ministry of Public Works* to diarists in the STUS, since diarists report region of residence at the time of the interview. Even though we follow labour models (e.g. Gubits, 2004; Black et al., 2008), it could be argued that residence location is endogenous, and that housing prices are also endogenous to labour market supply decisions. Hence, we use lagged and future regional housing prices. In this way, we use the following two instruments: mean housing prices in the term previous to the time use interview (*lagged housing*) and, secondly, mean housing prices in the term following the time use interview (*future housing*).[4]

Alternatively, we estimate an IV tobit model to account for censorship in reported time in the labour market. The 2-equation model can be written as follows:

$$l_i^* = \alpha_t + \beta_{1t} Commuting_i + \beta_{2t} X_i + \beta_{3t} Z_i + \alpha_t Day_i + \varepsilon_{it} \quad (3)$$

$$Commuting_i = \alpha_h + \beta_{1h} IV_i + \beta_{2h} X_i + \beta_{3h} Z_i + \alpha_h Day_i + \varepsilon_{ih} \quad (4)$$

where *li** is the latent number of hours a diarist would choose to spend in the labour market. The actual observed hours, *li* will equal zero when *li** is less than zero, and *li* will equal 24 when *li** is more than 24. The fact that we have limited the sample to diarists with at least one hour of *Market Work* means that the censorship at zero hours is not present, and we have no individuals reporting 24 hours of market work. Thus, we expect to obtain very similar results to the results obtained with equations (1) and (2).

We must now analyze whether these variables are good candidates to be instruments for *Commuting*. Regarding the first condition, that instruments must be correlated with the endogenous explanatory variable, in regions where housing prices are higher (e.g,

[4] The STUS covers the period from the fourth term of 2002 to the third term of 2003. See Table A1 in Appendix for a description of mean prices of housing in Spanish regions over the relevant period.

Madrid and Barcelona in the Spanish case), people may find it easier to live in non-urban areas, *ceteris paribus*, to alleviate the problem of high housing prices. To the extent that economic activities are mostly concentrated in urban areas, those living in non-urban areas will probably have a longer commute than people living in urban areas. Thus, the higher the housing prices in the region, the higher the probability that the diarist lives in a non-urban area, and thus the greater the time devoted to commuting. The sample correlations between the time devoted to *Market work* and the instruments are 0.1447 and 0.1519 for *lagged housing* and *future housing*, respectively, showing a large positive relationship between the instruments and the time devoted to *Commuting*.

Regarding the second condition, that instruments cannot be correlated with the error term in the explanatory equation, since instruments are obtained from regional data, we do not expect to have a correlation between the time devoted to *Market Work* and the instruments. The sample correlations between the time devoted to *Market work* and the instruments are 0.0244 and 0.0261 for *lagged housing* and *future housing*, respectively, which confirms that the instruments are not correlated with *Market Work*.

Regarding the included instruments (X_i, Z_i and Day_i), we include the variables that are common in time use studies, i.e., age (and its square), gender, university education, secondary education, living in couple (married/cohabiting), living in urban area, health status (dummy variables indicating whether the diarist reported having "very good health", "good health" or "fair health"), household composition (log of the number of family members, the number of children under 18, and the presence of children under 5, between 5 and 12, and between 13 and 17), household income (dummy variables to control for the different income groups), and whether the household owns the dwelling. See Kalenkoski et al. (2005,2007), Connelly and Kimmel (2007,2009), and Bloemen et al. (2010) for examples of variables used as controls in time use studies.

Additionally, we need to control for the type of occupation (e.g., Gimenez-Nadal et al., 2011), since it could be that the number of hours supplied by the individual is in fact a function of the type of work, rather than an individual choice. For instance, if the individual is opening a new restaurant, the individual would be less likely to be flexible than a regular employee in the hours of market work supplied. Also, the type of commitment required by so-called 'high-powered' jobs, such as law or medicine, may require a significant amount of up-front time in order to become established, so such individuals may also work longer hours. We control for the following occupations: 1)

Management, business, financial 2) Finance/legal professional 3) Science/engineering professional 4) Civil and social services 5) Education professional 6) Medical professional 7) Other professional 8) Health/social care support 9) Clerical or office support 10) Security and armed forces 11) Sales and services 12) Farming or forestry 13) Construction, assembly, and 14) Self-employed non-professional. We also control for whether respondent work in the public sector, or not.[5]

Table 1 shows means and standard deviations of the explanatory variables. Males comprise 60% of the sample, the mean age is 40 years, 30% of respondents have university education, 2% report having "fair health", the number of children is 0.84 per respondent, 85% of the respondents own the dwelling, 60% of the respondents have a net household income between 1,000€ and 2,000€ per month, 19% work in the public sector, and more than half of the sample work in finance/legal professions, farming or forestry, and self-employed non-professionals. We observe no statistically significant difference for these variables between all the respondents, and respondents with positive commuting time.

4. RESULTS

Columns (1) and (2) of Table 2 show the results of estimating GMM/IV linear and tobit models on the time devoted to *Market Work*, respectively.[6] Once we control for endogeneity, we observe a positive association between *Commuting* and *Market Work* per working day, with this association being statistically significant at the 99% level. Thus, one hour of *Commuting* is associated with 35 more minutes of *Market Work* during the working day. We interpret this positive association as a causal impact, since GMM/IV estimation allows us to obtain estimates of *Commuting* free of endogeneity problems.

However, if we want to accept the results of the GMM/IV analyses, we have to check whether we must estimate using the 2SLS/IV estimator or the GMM/IV estimator, whether it is necessary and useful to use IV (the relevance of the instruments), whether

[5] We follow the classification included in the Multinational Time Use Study (MTUS) version of the Spanish data. See www.timeuse.org for a detailed description of the MTUS dataset.

[6] See Table A2 for a description of the GMM/IV first stage results.

we have used the appropriate instruments (the validity of the instruments), and whether the quality of the instruments is sufficient.[7]

First, we apply the test to see whether the disturbance is homoskedastic or not.[8] To that end, we estimate the linear model using the 2SLS/IV estimator, and apply the Pagan-Hall test of heteroskedasticity for instrumental variables estimation (e.g., Pagan and Hall, 1983). Under the null hypothesis (that the disturbance is homoskedastic), the Pagan-Hall statistic is distributed as chi-squared with degrees of freedom equal to the number of indicator variables (e.g., $\chi^2(45)$). In our case, the Pagan-Hall statistic is 944.665, with a p-value of 0.00. Thus, we have heteroskedastic disturbances, and we choose the GMM/IV 2-step estimator. The Generalized Method of Moments (GMM) introduced by Hansen (1982) makes use of the orthogonality conditions to allow for efficient estimation in the presence of heteroskedasticity of unknown form, generating efficient estimates of the coefficients, as well as consistent estimates of the standard errors.

The Hansen test is a test of over-identifying restrictions. For the efficient GMM/IV estimator, the test statistic is Hansen's J-statistic, the minimized value of the GMM/IV criterion function. The joint null hypothesis is that the instruments are valid instruments, that is to say, they are uncorrelated with the error term and, secondly, the excluded instruments are correctly excluded from the estimated equation. Under the null, the test statistic is distributed as chi-squared in the number of over-identifying restrictions (e.g., $\chi^2(1)$). A rejection casts doubt on the validity of the instruments. In our case, the Hansen's J-statistics yield a value of 2.325, and a p-value of 0.1273, confirming that our instruments are valid at the 99% level.

The Anderson canonical correlations likelihood-ratio test, and the Cragg-Donald test are used to test whether the equation is identified. The statistic provides a measure of instrument relevance, and rejection of the null indicates that the model is identified. The null hypothesis of the tests is that the matrix of reduced form coefficients has rank of K-1, where K is the number of regressors. Under the null hypothesis of underidentification, the two statistics are distributed as chi-squared with degrees of

[7] References to the tests applied after the GMM/IV estimation can be found in Baum et al. (2003), Cushing and McGarvey (1999), Davidson and MacKinnon (1993), Hall et al. (1996), Hayashi (2002), Hansen et al. (1996), Shea (1997), Stock and Yogo (2002), and Wooldridge (2002).

[8] We focus on the linear IV model, since results for the tobit IV model are indistinguishable.

freedom of (L-K+1), where L is the number of instruments and K is the number of endogenous regressors (e.g., $\chi^2(2)$). In our case, the Anderson and Cragg-Donald statistic yield a value of 358.85, and a p-value of 0.00, indicating that the model is identified.

We also include the Anderson-Rubin Wald test of the significance of the endogenous regressors in the structural equation being estimated, where the null hypothesis is that the coefficients of the endogenous regressors in the structural equation are jointly equal to zero. The chi-squared version of the statistic is distributed with 2 degrees of freedom (e.g., $\chi 2(2)$), and it yields a value of 14.88, and a p-value of 0.0006, rejecting the null hypothesis at the 99% level.

Finally, we report the F-stat form of the Cragg-Donald statistic, suggested by Stock and Yogo (2002) as a test for the presence of weak instruments (i.e., that the equation is only weakly identified). The value of the statistic is 180.95, indicating that we can reject the presence of weak instruments.

Thus, we find a positive causal impact of *Commuting* time on the hours worked during a working day, with one hour of commuting increasing the time devoted to the labour market by 35 minutes. Throughout our analysis we have dealt with endogeneity problems. These results shed light on the relationship between commuting costs (time) and labour market behaviour during a working day, and we argue that both daily and weekly labour supply should be considered in theoretical models to provide a comprehensive view of commuter behaviour.

5. CONCLUSIONS

This paper analyses the causal effect of commuting time on labour supply patterns using data from the Spanish Time Use Survey 2002-03, which allows us to focus on the relationship between daily commuting and daily hours supplied to the labour market. We deal with the endogeneity of commuting time using GMM/IV models, where housing prices in the terms before and after the time of the interview are used as instruments. We show that commuting time increases daily labour supply, since one hour of commuting increases by 35 minutes the time devoted to the labour market during a working day. In doing so, we hypothesize that housing prices determine residence location decisions, although such decisions are exogenous following labour models (e.g. Gubits, 2004; Black et al., 2008).

A common assumption in the urban economic literature is that private costs of commuting are fully borne by the worker and do not affect the worker's productivity. However, urban efficiency wage theories allow that worker's work effort is a function of the length of the commute (Zenou, 2002; Ross and Zenou, 2008). Our results are in line with urban efficiency wage theories, in the sense that there is a significant causal impact between commuting and worker's labour supply. Furthermore, we argue that both daily and weekly labour supply should be considered in urban efficiency wage models to provide a comprehensive view of commuter behaviour.

We acknowledge that our results are limited by the fact that we cannot control for individual unobserved heterogeneity. While some authors consider that there is an involuntary relationship between workers' productivity and commuting (Koslowsky et al. 1995; Zenou, 2002), others consider that there is a voluntary relationship between workers' productivity and commuting (Ehrenberg, 1970), and thus individual unobserved heterogeneity may be a crucial factor in determining the workers' behaviour. However, Gutiérrez- i-Puigarnau and van Ommeren (2010) use panel data for Germany and find that commuting distance slightly increases daily and weekly labour supply, and that the number of workdays is not affected. Thus, our results, although limited by the structure of the data, are consistent with those of Gutiérrez- i-Puigarnau and van Ommeren (2010). To the best of our knowledge, this is the first paper to adopt a time use perspective in the study of commuting costs and labour market behaviour.

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Table 1. Summary Statistics [1,2,3]

	All Respondents		Respondents Commuting>0	
Time Use Variables (hours per day)	Mean	S.D.	Mean	S.D.
Market Work	7.736	(0.019)	7.824	(0.019)
Commuting	0.954	(0.006)	1.030	(0.006)
ExplanatoryVariables				
Male	59.863	(0.392)	60.218	(0.408)
Age	40.372	(0.084)	40.098	(0.087)
University education	31.007	(0.371)	31.167	(0.387)
Secondary education	53.476	(0.400)	53.683	(0.416)
Living in couple	71.207	(0.362)	70.948	(0.377)
Living in urban area	57.948	(0.395)	59.049	(0.409)
Fair Health	2.279	(0.120)	2.235	(0.123)
Good health	14.015	(0.278)	13.791	(0.288)
Very good health	54.993	(0.398)	55.065	(0.414)
Log family members	1.218	(0.003)	1.219	(0.003)
Number of children <18	0.837	(0.008)	0.840	(0.008)
Youngest child 0-4	0.199	(0.003)	0.201	(0.003)
Youngest child 5-12	0.198	(0.003)	0.198	(0.003)
Youngest 13-17	0.118	(0.003)	0.120	(0.003)
Home ownership	84.895	(0.286)	84.895	(0.286)
Hhld income <500€	1.416	(0.095)	1.237	(0.092)
Hhld income 500-999€	11.286	(0.252)	11.093	(0.261)
Hhld income 1000-1250€	23.485	(0.339)	23.508	(0.353)
Hhld income 1250-1500€	22.054	(0.332)	22.450	(0.348)
Hhld income 1500-2000€	16.265	(0.295)	16.454	(0.308)
Hhld income 2000-2500€	10.267	(0.243)	10.377	(0.254)
Hhld income 2500-3000€	12.578	(0.266)	12.436	(0.276)
Hhld income +3000€	2.649	(0.260)	85.124	(0.296)
Public sector	18.578	(0.312)	19.008	(0.328)
Management, business, financial	0.947	(0.077)	0.914	(0.079)
Finance/legal professional	14.366	(0.281)	14.033	(0.290)
Science/engineering professional	4.836	(0.172)	4.829	(0.179)
Civil and social services	4.289	(0.163)	4.346	(0.171)
Education professional	1.562	(0.099)	1.556	(0.103)
Medical professional	4.176	(0.162)	4.025	(0.166)
Other professional	2.855	(0.133)	2.926	(0.139)
Health/social care support	2.111	(0.115)	1.942	(0.115)
Clerical or office support	3.808	(0.153)	3.895	(0.160)
Security and armed forces	6.222	(0.195)	6.537	(0.207)
Sales and services	2.595	(0.127)	2.655	(0.133)
Farming or forestry	21.329	(0.326)	21.453	(0.340)
Construction, assembly	5.147	(0.175)	4.346	(0.168)
Self-employed non-professional	25.757	(0.168)	26.543	(0.173)
Observations	15,798		14,682	

Notes: [1] Standard deviations in parentheses [2] Sample consists of respondents aged 21-65 from the Spanish Time Use Survey 2002-2003 [3] Time devoted to time use activities is measured in hours per day.

Table 2. GMM/IV estimates on hours per day devoted to *Market Work*[1,2,3,4,5]

Market Work (Hours per day)	Linear Gmm/IV	Tobit GMM/IV
Commuting time	0.578***	0.596***
	(0.17)	(0.17)
Male	1.256***	1.254***
	(0.05)	(0.05)
Age	0.056***	0.055***
	(0.02)	(0.02)
Age squared	-0.068***	-0.067***
	(0.02)	(0.02)
University education	-0.101	-0.110
	(0.07)	(0.07)
Secondary education	-0.080	-0.083
	(0.06)	(0.06)
Living in couple	-0.106**	-0.105*
	(0.05)	(0.05)
Living in urban area	-0.171***	-0.174***
	(0.05)	(0.05)
Fair Health	-0.033	-0.036
	(0.14)	(0.15)
Good health	-0.042	-0.040
	(0.06)	(0.06)
Very good health	-0.010	-0.007
	(0.04)	(0.04)
Log family members	-0.040	-0.045
	(0.06)	(0.06)
Number of children <18	0.042	0.047
	(0.04)	(0.04)
Youngest child 0-4	-0.190**	-0.199**
	(0.09)	(0.09)
Youngest child 5-12	-0.169**	-0.172**
	(0.08)	(0.08)
Youngest 13-17	-0.026	-0.033
	(0.08)	(0.08)
Home ownership	-0.054	-0.053
	(0.05)	(0.06)
Public sector	-0.577***	-0.572***
	(0.06)	(0.06)
Constant	5.509***	5.484***
	(0.36)	(0.36)
R-squared	0.152	-
Observations	15,798	15,798

Notes: [1] Robust standard errors in parentheses [2] Sample consists of respondents aged 21-65 from the Spanish Time Use Survey 2002-2003 [3] Time devoted to time use activities is measured in hours per day [4] We include dummy variables to control for day of the week (Ref.: Saturday), occupation (Ref.: Self-employed non-professional) and net-monthly household income (Ref.: Hhld income +3000€) [5] *$p < .10$ **$p < .05$ *** $p < .01$

APPENDIX

Table A1. Housing prices by Spanish region (in Spanish)

Regional housing prices	2002		2003			
	Term		Term			
	3rd	4th	1st	2nd	3rd	4th
Andalucía	926.5	932.1	983.6	1037.8	1090.7	1121.3
Aragón	1084.5	1130.8	1117.4	1186.1	1199.5	1256.3
Asturias (Principado de)	1058.1	1102.3	1116.5	1133.6	1167.8	1227.6
Baleares	1468.7	1508.4	1531.1	1567	1618	1631.2
Canarias	1184.6	1209	1241	1268.5	1311.3	1329.6
Cantabria	1245.1	1287.3	1308.4	1324.6	1387.9	1435
Castilla y León	959.7	962.2	970.8	1001.5	1040.8	1053.1
Castilla la Mancha	778.1	791.1	820.6	857.2	889.1	929.2
Cataluña	1363.9	1410.2	1456.5	1520.1	1562.6	1632
Comunidad Valenciana	953	975.9	1011	1054.2	1085.2	1112.2
Extremadura	608	611.3	627.2	651.5	674.9	695.8
Galicia	873.9	886.5	898	910.5	952.9	987.2
Madrid	1727.5	1868.8	1936.9	2018	2122.7	2185.5
Región de Murcia	801	837	848.1	878	945	987.2
Comunidad Foral de Navarra	1232.8	1255.7	1258.8	1310.9	1341.5	1343
País Vasco	1906.8	1948.3	2026.6	2082.8	2102.4	2107.2
La Rioja	1044.4	1079.3	1131.1	1174.4	1142.2	1192.6
Spain	1142.7	1164.6	1230.3	1309.6	1344.9	1380.3

Notes: [1] *Source*: Ministry of Public Works [2] Regional housing prices are measured in €/m^2

Table A2. First stage GMM/IV estimations[1,2,3,4,5]

Commuting (hours per day)	Linear Gmm/IV	Tobit GMM/IV
Lagged housing	-0.002***	-0.002***
	(0.000)	(0.000)
Future housing	0.002***	0.002***
	(0.000)	(0.000)
Male	0.112***	0.112***
	(0.013)	(0.013)
Age	0.001	0.001
	(0.004)	(0.004)
Age squared	-0.006	-0.006
	(0.005)	(0.005)
University education	0.014	0.014
	(0.022)	(0.022)
Secondary education	-0.028*	-0.028*
	(0.017)	(0.017)
Living in couple	-0.005	-0.005
	(0.015)	(0.015)
Living in urban area	0.127***	0.127***
	(0.012)	(0.012)
Fair Health	0.020	0.019
	(0.037)	(0.037)
Good health	0.023	0.023
	(0.019)	(0.019)
Very good health	0.014	0.014
	(0.013)	(0.013)
Log family members	0.044**	0.044**
	(0.018)	(0.018)
Number of children <18	-0.025*	-0.025*
	(0.013)	(0.013)
Youngest child 0-4	-0.059**	-0.058**
	(0.029)	(0.029)
Youngest child 5-12	-0.013	-0.013
	(0.026)	(0.026)
Youngest 13-17	0.014	0.014
	(0.023)	(0.023)
Home ownership	0.012	0.012
	(0.016)	(0.016)
Public sector	-0.054***	-0.054***
	(0.017)	(0.017)
Constant	0.370***	0.372***
	(0.102)	(0.102)
R-squared	0.717	-
Observations	15,798	15,798

Notes: [1] Robust standard errors in parentheses [2] Sample consists of respondents aged 21-65 from the Spanish Time Use Survey 2002-2003 [3] Time devoted to time use activities is measured in hours per day [4] We include dummy variables to control for day of the week (Ref.: Saturday), occupation (Ref.: Self-employed non-professional) and net-monthly household income (Ref.: Hhld income +3000€) [5] *$p < .10$ **$p < .05$ *** $p < .01$.