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J. González Chapela*

Abstract

This study uses a simple job-design model and the 2002-2003 Spanish Time Use Survey to establish the existence of a previously overlooked relationship between physical work intensity and the split workday. The theoretical model predicts that the incidence of working split shifts may increase with physical work intensity if and only if the degree of recovery allowed by the mid-workday break is directly proportional to the physical load of the work done. Occupation-specific estimates of energy expenditure are constructed for Spain which permit investigating empirically the determinants of the split workday and the length of the mid-workday break.

Key words: Split workday, work recovery, metabolic equivalent value, Spanish Time Use Survey.

JEL classification: J22, J81.

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1. INTRODUCTION

A prominent feature of the Spanish labor market is that a large number of individuals work split shifts, consisting typically of 5 hours' work in the morning, a 2-hour break at lunch time, and another 3 hours' work in the afternoon/evening. According to the Spanish Survey of Working Conditions, 52.2% of workers were on a daytime split work schedule in 2003, and 40.2% in 2011 (INSHT 2003, 2011). As a result, compared to other OECD countries, the distribution of working hours in Spain is quite wide and features a sharper dip in the middle of the day (see, e.g., Amuedo-Dorantes and de la Rica 2009).

A growing literature has investigated the consequences that working split shifts may have for a variety of socio-economic outcomes.[1] Gutiérrez-Domènech (2010) and Gracia and Kalmijn (forthcoming) have observed strong negative associations at the individual level between working split shifts and time spent on childcare, and suggested that the split workday may be detrimental for a child's cognitive development (see also Del Boca et al. 2014). Working split shifts may have a bearing on the fact that the Spanish employment gender gap is one of the highest among OECD economies (Guner et al. 2014), as the split workday complicates the scheduling of family activities (Gracia and Kalmijn forthcoming) and makes family and work less compatible. Another characteristic that has been associated to the split workday is the relatively lower productivity of Spanish workers (ARHOE 2013), a conjecture that has received mixed support from large-scale evidence on hourly wages (Amuedo-Dorantes and de la Rica 2009, Montañés Bernal 2011, González Chapela 2015), but has been borne out by sectoral and establishment-level data on value added and employment (Montañés Bernal 2011).

Despite its apparent importance for topics of undoubted scientific and public policy interest, little is still known about what determines the split/straight decision. Some observers have argued that the split workday in Spain had its origin in the post-civil war period, when many individuals needed to hold down two jobs, one in the morning and other in the afternoon (e.g., see Barbería 2014). But while moonlighting might have settled the habit of a long mid-workday break among the Spanish labor force, the previous argument does not explain why seemingly straight-

[1] This literature is part of a larger body of research concerned with the consequences of non-standard work hours. See, among others, Presser (1988, 1994), Kostiuk (1990), Bryson and Forth (2007), Rapoport and Le Bourdais (2008), Williams (2008), and Brachet et al. (2012).

shifted jobs became split-shifted.[2] Furthermore, recent evidence suggests that the split workday may be demand-driven, as the distribution of workers across industries and occupations differs by workday type, but is similar across household income groups (Montañés Bernal 2011, González Chapela 2015).

Beyond the interest that the topic may have for its own sake, it is unlikely that reforms of work schedules be effective without knowing the determinants of these. To contribute toward filling this knowledge gap, this paper analyzes both theoretically and empirically whether the split workday is a means of managing workers' fatigue and thus saving costs to firms. The fundamental premise of this research is twofold: Although strenuous physical exertion has been all but eliminated from most occupations, significant differences in physical work intensity still prevail (Tudor-Locke et al. 2009, 2011; Zavodny 2015). And since exerting effort on a job task consumes energy and is thus fatiguing, workers are to be compensated for the disutility created by fatigue and allowed to take within-day work breaks (Weiss 1996, Nocetti 2008, Dragone 2009, Brachet et al. 2012, Marchetti and Nucci 2014).[3]

The determinants of the split workday are analyzed in the framework of the theory of equalizing differences (see Rosen 1986), albeit switching this theory's main focus from explaining wage differences to investigating the role of the split workday in reducing wage compensations. Essentially, my main argument is that the type of workday is rationally chosen by personnel managers trying to minimize the compensation paid to workers. These are to be compensated for the travel to work, the accumulated fatigue due to physical job requirements, and the fact of working at non-standard hours. The mid-workday break provides recovery from fatigue, with recovery assumed to be increasing (and thus compensation paid decreasing) in the length of the break. However, a long mid-workday break increases the travel to work and stretches the workday to non-standard hours, so that personnel managers must consider which of workday types to implement.

Physical activity is often measured in terms of energy expenditure, which in turn is very frequently expressed as metabolic equivalent (MET) values (Montoye et al. 1996). In this paper I construct occupation-specific MET estimates for Spain, which

[2] I use "mid-workday break" rather than "lunch break" because only 29.5% of straight-shift workers report having lunch within the workday, compared to 93.2% in the case of split-shifters.

[3] The accumulation of fatigue can also be viewed as impairing workers' performance, which is indeed the perspective adopted by Dragone (2009) and Brachet et al. (2012).

are then matched to national individual-level observations of workday type to investigate empirically the determinants of the split workday. Furthermore, and because the existence of an observed association between the split workday and occupational energy expenditure is only suggestive of an effect of the latter on the duration of the mid-workday break, this break's length is also analyzed empirically. Since all workers within an occupation are assigned the same MET estimate and some surveyed households contribute more than one member to the sample, inference is made robust to regression errors clustered by occupation and household (Hersch 1998, Cameron and Miller 2015).

The study of when we work has received increased attention since the seminal works of Winston (1982) and Hamermesh (1996). The range of topics investigated is quite broad and includes, for example, the synchronization/coordination of work schedules (Weiss 1996, Hamermesh et al. 2008), evening/night/weekend work (Hamermesh 1999, Hamermesh and Stancanelli 2015), shiftwork (Mayshar and Halevy 1997, García and Vázquez 2005, Jirjahn 2008), and flexible work schedules (McMenamin 2007, Golden 2012). This paper contributes to this literature by establishing a previously overlooked relationship between physical work intensity and the split workday.

The rest of the paper is organized as follows. Section 2 develops the basic theoretical model and discusses some extensions. While this model's predictions are applied to the case of the Spanish labor market, they might also be relevant for explaining cross-country differences in the prevalence of the split workday, an interesting issue that is left for future research. Section 3 describes the data sources, the sample selection, and the construction of the key variables. The econometric methodology used in the empirical analysis is discussed in section 4. The main empirical results and a number of robustness checks are presented in section 5. Section 6 concludes.

2. PHYSICAL WORK INTENSITY AND THE SPLIT WORKDAY: ESTABLISHING A CAUSAL EFFECT

A personnel manager is setting the work schedule of a job. Suppose that, in order to exploit positive interactions with other workers in the firm or in the industry (Weiss 1996, Hamermesh et al. 2008), the work has to be done in the daytime under a straight or split schedule. The straight schedule consists of 5 hours' work in the morning starting at 9 am, a 30-minute break at 2 pm, and 3-hours back at work until

5:30 pm. The split schedule features a 2-hour break at 2 pm, which stretches the workday until 7 pm. The manager is choosing the work schedule that minimizes the payment given to the worker, who must be compensated for the travel to work plus the (undiscounted) sum of momentary disutilities created by fatigue and the condition of working at nonstandard hours.

The momentary disutility resulting from fatigue is modeled as

$$f\left(h;l,\kappa\right)=\begin{cases}\kappa h & \text{for } 0\leq h\leq 5\\ \kappa\left(h-l\right) & \text{for } 5<h\leq 8\end{cases} \tag{1}$$

where h denotes the number of hours worked since 9 am, l is the duration of the mid-workday break, and κ ($\kappa>0$) stands for the intrinsic physical load of the work done.[4] As in the classic studies of Chapman (1909) and Ramsbottom (1914), fatigue is increasing in h, but, additionally, it is compounded by κ (Ramsbottom 1914 and Nocetti 2008). The mid-workday break provides recovery from fatigue. Recovery is deemed to be increasing in the length of the break, as most of the available evidence suggests that longer breaks are more effective in managing fatigue (Tucker 2003, Arlinghaus et al. 2012, Lombardi et al. 2014). Furthermore, and following Tucker (2003), fatigue-reduction effectiveness is assumed to be influenced by the nature of the work done: In expression (1), that reduction is larger the larger is κ, but other possibilities will be discussed as well.

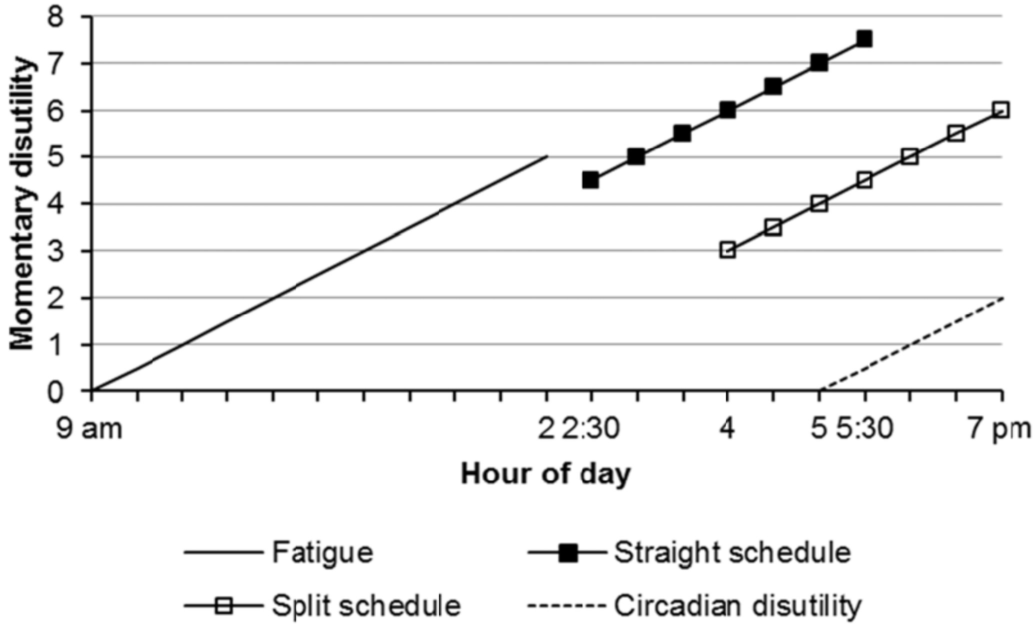
The momentary disutility of working at nonstandard hours is assumed to be derived from physiological and possibly psychological and social rhythms that may dictate schedules of work and rest (Alluisi and Morgan 1982). It will be referred to as circadian disutility, and is modeled as

$$g\left(\bar{h};\gamma\right)=\gamma\bar{h}, \tag{2}$$

where $\bar{h}$ is the number of hours worked since (say) 5 pm and γ ($\gamma>0$) denotes a preference parameter for not working at nonstandard hours. γ would seem to be larger for parents whose children end school in the early evening, and lower for workers sorted into long-hours workplaces (Bryan 2007), for example. Functions (1) and (2) are depicted in Figure 1 for the case $\kappa=\gamma=1$. The area below the curves yields the accumulated disutility over the workday.

[4] All of these dimensions are given to the worker. Marchetti and Nucci (2014) consider a related case with variable effort and hours.

Figure 1. Momentary disutility on the job



When the residential and job locations do not coincide and commuting is a necessity, a worker incurs commuting costs. In Spain, the average duration of the commute is similar for split- and straight-shift workers, but split-shifters' mean number of daily commutes is larger (see Table 2 below), partly because the proportion of workers who eat at home increases in the split workday (González Chapela 2015). Hence, the disutility from commuting will be assumed to be larger under a split schedule, with the size of the gap with respect to the straight workday being given by ξ ($\xi > 0$).

For all these reasons, the total disutility of a straight workday is

$$30.5\kappa + 0.125\gamma, \tag{3}$$

whereas that of the split workday is

$$26\kappa + 2\gamma + \xi. \tag{4}$$

The manager chooses the split workday whenever (3) > (4), which occurs when

$$\kappa > 0.417\gamma + 0.222\xi. \tag{5}$$

Therefore, for given γ and ξ, the higher κ the higher the likelihood of adopting the split workday. Or, in other words, the incidence of working split shifts is increasing in the physical load of the work done, ceteris paribus. This conclusion would be preserved if h and $(h-l)$ in expression (1) were raised to a positive exponent other than 1. However, it would be reversed if recovery were inversely proportional to κ, because if

$$f\left(h;l,\kappa\right)=\kappa h-\kappa^{-1}l \quad \text{for } 5<h\leq 8\,, \tag{6}$$

the split workday would be chosen whenever

$$\kappa<\frac{4.5}{1.875\gamma+\xi}\,. \tag{7}$$

Note also that if recovery were unrelated to κ,

$$f\left(h;l,\kappa\right)=\kappa h-l \quad \text{for } 5<h\leq 8\,, \tag{8}$$

the type of workday would be unaffected by κ.

The model of fatigue assumed in this paper abstracts from a number of interesting features. Fatigue is believed to decrease in the early morning due to a warm-up effect (Alluisi and Morgan 1982, Booth and Ravallion 1993, García and Vázquez 2005), but since the morning period is common to both types of workday, the inclusion of this characteristic would not alter the main conclusion. For simplicity, (1) does not allow recovery to be influenced by the type of activities undertaken during the mid-workday break (Trougakos and Hideg 2009). Nor does it include the post-lunch dip in productivity because the effect of meal duration on performance is unclear (Alluisi and Morgan 1982). Another important limitation is that fatigue could benefit from dividing the mid-workday break into shorter breaks (Tucker 2003). Suppose, for example, that the 2-hour break were replaced with a 1-hour break at 2 pm plus four (unpaid) rest breaks of 15 minutes at 10:30 am, 12:15 pm, 4:15 pm, and 5:45 pm. In this case, the resulting total disutility would be

$$24.8125\kappa+2\gamma+\xi\,, \tag{9}$$

which is lower than (4). Shorter breaks and the type of activities undertaken during the mid-workday break will be taken into account in the empirical part.

3. DATA

The primary source of data for exploring empirically the linkage between physical work intensity and the split workday is the 2002-2003 Spanish Time Use Survey (STUS), a nationally representative survey of individual time allocation conducted by the Spanish Statistical Office (INE). To avoid seasonal distortions, the STUS size was distributed evenly between October 2002 and September 2003. Persons living in the interviewed households who were at least 10 years old were asked to list their main activity in every 10-minute interval of the previous 24-hour day (beginning at 6 am). These activities were then classified into standardized codes (listed in Annex VI of Eurostat 2004). The STUS also collected demographic and labor market information by means of additional questionnaires, including, if the respondent was working, the type of workday and occupation.

The main explanatory variable of this study is the MET value of every individual's occupation. A MET value represents the ratio of an activity energy expenditure to the resting energy expenditure, with lying or sitting quietly classified as 1 MET (Montoye et al. 1996). Thus, for example, a 3-MET activity requires 3 times the energy expenditure at rest. Commissioned by the National Cancer Institute, U.S. National Institute of Health, Tudor-Locke et al. (2009, 2011) have assigned MET summary values to 485 detailed occupations distinguished in the 2002 occupational classification system (OCS) of the U.S. Census Bureau. To do this, Tudor-Locke et al. considered the specific movements characterizing each occupation, classified in terms of body position (sit, stand, walk, heavy labor) and intensity or pace (light, moderate, vigorous). An occupation's MET summary value was then obtained by averaging the METs assigned to the occupation's typical movements. The resulting set of MET estimates was accessed online at http://riskfactor.cancer.gov/tools/ocs-met/ on February, 23 2015.[5]

In the 2002-2003 STUS, the respondent's occupation was classified according to INE's 1994 National Classification of Occupations (CNO-94), broken down at the level of 228 categories pertaining to 21 Main Subgroups and 207 Subgroups of the CNO-94.[6] To assign a MET value to each of these occupational categories, I followed an aggregation process similar to that carried out by Tudor-Locke et al. (2009). Specifically, each Subgroup of the CNO-94 comprises one or more Primary Groups, which provide the highest level of detail in the hierarchical structure of the CNO-94.

[5] Tudor-Locke et al. (2009) also assigned MET values to every activity distinguished in the American Time Use Survey (ATUS), which have been used to investigate the relationship between gasoline prices and physical activity (Sen 2012), energy expenditure in women (Archer et al. 2013), and the impact of the business cycle on individuals' physical activity (Colman and Dave 2013). An alternative measure of objective physical job requirements, derived from the O*NET 4.0 database (http://onetcenter.org), was used by Zavodny (2014) to examine whether immigrants hold more physically demanding jobs than U.S. natives. Zavodny's measure seems superior to MET summary values in that it combines time spent on seven different body positions, although, on the other hand, it does not incorporate information about intensity or pace. In addition, O*NET 4.0 data on physical work conditions is not available for 22.8% of the occupational categories.

[6] In the more recent 2009-2010 STUS, the occupation was recorded with a much lower level of detail. This is the main reason why the current analysis focuses on 2002-2003 survey.

To each of the 482 distinct Primary Groups, I assigned the MET value of the closest OCS detailed occupation with available MET summary value. Then, a MET value was computed for each Subgroup (respectively, Main Subgroup) by averaging the MET values assigned to the underlying Primary Groups (Subgroups).

Table 1 presents an example of this process illustrating some of the difficulties encountered.[7] 57.1% of the Primary Groups presented an obvious OCS equivalent (for example *"Techadores"* and *Roofers*), so that the MET of the latter was assigned. 28.2% went into more than one OCS detailed categories, as for example *"Pintores, barnizadores, empapeladores y asimilados"*, whose description in INE (1994) closely matched that of *Painters, construction and maintenance* (MET = 4.00) and *Paperhangers* (MET = 3.50). In these cases, the average MET value of the OCS categories (3.75) was assigned. For the remaining 14.7%, which did not present obvious OCS equivalents, the OCS occupation(s) whose description at www.bls.gov/soc/2000/socguide.htm seemed closest to the examples and descriptions given in INE (1994) was assigned. For example, *Painters, construction and maintenance* and *Sewer pipe cleaners* were assigned to *"Personal de limpieza de fachadas de edificios y deshollinadores"*, and *Elevator installers and repairers* was assigned to *"Otros trabajadores diversos de acabado de construcciones"*. The complete crosswalk between the CNO-94 and the 2002 OCS is available from the author upon request.

[7] The CNO-94 lay within the ISCO-88 framework, whereas the Census 2002 OCS was based on the 2000 Standard Occupational Classification (SOC). Both systems classified occupations based on work performed and on required skills, but the latter applied additionally the concept of "job families", whereby people who work together are classified in the same group regardless of their skill level (Scopp 2003). The complete structure of the CNO-94 was accessed at www.ine.es/clasifi/cno94.xls on May, 3 2015. Additionally, INE (1994) provided examples of occupations which do and do not fall under each Primary Group, but to which no specific codes were assigned. The 2000 SOC arranged occupations into 23 major groups and 821 detailed categories, which are described at www.bls.gov/soc/2000/socguide.htm. The U.S. Census then aggregated the detailed SOC categories into 509 detailed census categories within the same 23-major group framework. The crosswalk for comparing data from 2002 OCS to 2000 SOC was accessed at www.census.gov/people/io/files/occ2000t.pdf on May, 5 2015.

TABLE 1—EXAMPLE OF MET VALUES ASSIGNED TO INE'S 1994 NATIONAL CLASSIFICATION OF OCCUPATIONS

STUS CODE	1994 NATIONAL CLASSIFICATION OF OCCUPATIONS		2002 CENSUS OCCUPATIONAL CLASSIFICATION SYSTEM		MET VALUE
	CODE	CATEGORY TITLE	CATEGORY TITLE (and associated MET value: Tudor-Locke et al. 2011)	CODE	
720	72	Trabajadores de acabado de construcciones y asimilados; pintores y otros asimilados			3.70
721	721	Revocadores, escayolistas y estuquistas			4.00
	7210	Revocadores, escayolistas y estuquistas	Painters, construction and maintenance (4.00); plasterers and stucco masons (4.00)	6420 6460	
722	722	Fontaneros e instaladores de tuberías			4.00
	7220	Fontaneros e instaladores de tuberías	Pipe layers, plumbers, pipe fitters, and steam fitters (4.00)	6440	
723	723	Electricista de construcción y asimilados			3.00
	7230	Electricista de construcción y asimilados	Electricians (3.00)	6350	
724	724	Pintores, barnizadores, empapeladores y asimilados			3.75
	7240	Pintores, barnizadores, empapeladores y asimilados	Painters, construction and maintenance (4.00); paperhangers (3.50)	6420 6430	
725	725	Personal de limpieza de fachadas de edificios y deshollinadores			3.75
	7250	Personal de limpieza de fachadas de edificios y deshollinadores	Painters, construction and maintenance (4.00); sewer pipe cleaners (3.50)	6420 6750	
729	729	Otros trabajadores de acabado de construcción y asimilados			3.70
	7291	Techadores	Roofers (3.50)	6510	
	7292	Parqueteros, soladores y asimilados	Carpet, floor, and tile installers and finishers (3.50)	6240	
	7293	Instaladores de material aislante térmico y de insonorización	Insulation workers (4.00)	6400	
	7294	Cristaleros	Glaziers (3.50)	6360	
	7299	Otros trabajadores diversos de acabado de construcciones	Elevator installers and repairers (4.00)	6700	

Abbreviations: MET, metabolic equivalent; INE, Spanish Statistical Office; STUS, 2002-2003 Spanish Time Use Survey.

The STUS occupation with the highest MET value (7.50) corresponded to freight, stock, and material movers by hand and loaders (*"Peones del transporte y descargadores"*), the occupational average MET (2.51) was close to the MET value for education occupations (2.50), and the lowest MET (1.50) prevailed among managerial and professional occupations. 24.1% of the STUS occupations comprised a Primary Group with no obvious OCS equivalent. These occupations will be removed to evaluate the robustness of the empirical results. Tudor-Locke et al. (2011) have classified occupations by intensity level into sedentary (<2 METs), light (2-2.99 METs), moderate (3-5.99 METs), and vigorous (≥6 METs). In this way, 56 of the STUS occupations appeared to be sedentary, 118 light, 52 moderate, and 2 vigorous (carpenters and the one cited above). As for the Primary Groups, the distribution was 130, 222, 124, and 6, respectively.

In this study, the effective number of STUS occupations is lower than 228 because the sample was restricted to full-time employees with just one job, aged 18-64, who did not work between 10 pm and 6 am in the observation day, and who considered that day to be a regular working day. The self-employed were discarded because the type of workday was asked of employees only, whereas restricting the sample to daytime workers with just one job was aimed at reducing heterogeneity. To be considered a full-time worker, an individual had to work more than 6 hours in the observation day and more than 30 hours per week. The sample was further restricted to regular working days because the occupation-level estimates of energy expenditure are considered a better reflection of the energy cost of an occupation as done during a usual workday (Tudor-Locke et al. 2009). Furthermore, this restriction was necessary to increase the reliability of the time-use measures utilized in this study. After removing cases with missing or inconsistent data, the resulting sample comprised 5773 workers (and as many time diaries), living in 4682 households and working in 197 occupations.

The main explaining variable is a binary indicator for the type of workday, constructed from the question *What kind of workday do you have: Split or straight?* 52.6% of the sample report working split shifts (the corresponding population percentage is 54.5). Table 2 presents some characteristics of split- and straight-shifters. Managers, supporting technicians/professionals, and manufacturing workers (including construction trades workers) are more prevalent among split-shifters, as is the prevalence of moderate and vigorous occupations. The occupational differences by physical work intensity are not statistically significant with the exception of that corresponding to light occupations, -8.9%, which attains significance at 10%. (Inference is cluster-robust; see the notes to Table 2 for details.) Analysis using MET values results in 0.24 more METs among split-shifters, a gap which is different from zero at 5%. While the sign and statistical significance of this gap suggest that the incidence of the split workday is increasing in the physical work intensity, its size is not large and could be the result of composition effects.

TABLE 2—WORKER CHARACTERISTICS BY TYPE OF WORKDAY

	Split (*N* = 3037)	Straight (*N* = 2736)	Difference
Occupation, by Large Group of the CNO-94 (%)			
Manager	3.0	1.5	1.5***
Technician/Professional	8.5	12.1	-3.6***
Supporting technician/professional	17.4	13.6	3.8***
Clerical worker	8.3	11.8	-3.5***
Service/Sales worker (incl. military)	13.6	16.7	-3.1***
Agricultural worker	1.2	1.4	-0.2
Manufacturing worker	27.5	16.4	11.1***
Operator	8.5	11.5	-3.0***
Unskilled worker	12.0	15.0	-3.0***
Occupation, by physical work intensity (%)			
Sedentary	31.8	30.4	1.4
Light	32.8	41.7	-8.9*
Moderate	32.3	26.4	5.9
Vigorous	3.1	1.5	1.6
Physical work intensity (METs)	2.86	2.62	0.24**
Breaks (min. per day)			
Main break non-working	105.9	31.6	74.3***
Main break resting	52.8	22.5	30.3***
Other (shorter) breaks non-working	9.3	3.9	5.4***
Other (shorter) breaks resting	11.3	4.0	7.3***
Commuting			
Travel-to-work time (min.)	24.8	26.5	-1.7***
No. of daily commuting episodes	3.2	2.1	1.1***

Notes: The table shows results for the complete sample of full-time employees observed in a regular working day. The last column shows the results of mean-comparison tests between split- and straight-shifters. The tests were performed regressing the variable indicated on the left-most column on a constant plus a dummy for split workday, whose coefficient measures the difference between split- and straight-shifters on the corresponding variable. The statistical significance of this difference was assessed by comparing the absolute value of a cluster-robust *t*-statistic with critical values from a standard normal distribution. For the occupational large groups, clustering was on household; for the other cases, clustering was on household and occupation (using the Stata user-written command *cgmreg*: Cameron and Miller 2015). *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.
Source: Spanish Time Use Survey, 2002-2003, INE.

The existence of a relationship between physical work intensity and the split workday is only suggestive of an effect of the former on the length of the mid-workday break. Hence, this break's length will be also analyzed. I construct two different measures of the mid-workday break because there is evidence that recovery is influenced by the types of activities engaged in during work breaks (Trougakos and Hideg 2009). The narrowest measure equates the mid-workday break to the main (i.e. longest) period of time resting within the workday. Rest time comprises breaks during working hours (tea and coffee breaks, breaks due to personal reasons, and lunch break) plus all other time spent napping, socializing, relaxing, eating and drinking, and doing sports or exercise between two working spells of the same workday. Napping, socializing, and relaxing were identified by Trougakos et al. (2008) as effective in fighting fatigue effects, whereas the ATUS explicitly separates socializing, relaxing, eating and drinking, and doing sports or exercise as part of job (i.e. with coworkers, clients, or customers) from working time, as work-relevant tasks are not expected.[8] The second, widest measure equates the mid-workday break to the main period of time non-working within the workday. Non-work time comprises rest time plus all other non-work-related tasks such as running errands or household chores. The observed lengths of the main breaks (given in Table 2) are much longer among split-shifters, and those corresponding to time non-working are close to those hypothesized in Section 2.

4. ECONOMETRIC METHODS

4.1 Type of Workday

A probit model is used to investigate the relationship between physical work intensity and the split workday. Let y_{1i}^{*}, a continuous random variable representing the propensity of worker i to be on a split workday, be given by

$$y_{1i}^{*} = \mathbf{x}_{1i}'\boldsymbol{\beta}_1 + u_{1i}, \qquad (10)$$

where $\mathbf{x}_{1i}$ is a vector of explanatory variables, $\boldsymbol{\beta}_1$ denotes an unknown parameter vector, and u_{1i} represents a standard normally distributed random error. The observed type of workday is indicated by the binary variable

$$y_{1i} = 1\left[y_{1i}^{*} > 0\right], \qquad (11)$$

[8] The ATUS activity classification system can be found at www.bls.gov/tus/lexicons.htm.

where the function $1[\cdot]$ equals one if its argument is true and zero otherwise. Thus, $y_{1i} = 1$ when i's workday is split, and $y_{1i} = 0$ when it is straight.

The probability of working split shifts is given by

$$P\left(y_{1i} = 1 \middle| \mathbf{x}_{1i}\right) = \Phi\left(\mathbf{x}_{1i}'\boldsymbol{\beta}_1\right), \tag{12}$$

$\Phi(\cdot)$ being the standard normal cdf. The probit estimate $\hat{\boldsymbol{\beta}}_1$ is obtained by maximizing $\sum_{i=1}^{N} \ell_i\left(\boldsymbol{\beta}_1\right)$, where

$$\ell_i\left(\boldsymbol{\beta}_1\right) = y_{1i} \log\Phi\left(\mathbf{x}_{1i}'\boldsymbol{\beta}_1\right) + \left(1 - y_{1i}\right)\log\left[1 - \Phi\left(\mathbf{x}_{1i}'\boldsymbol{\beta}_1\right)\right]. \tag{13}$$

Under standard assumptions, $\hat{\boldsymbol{\beta}}_1$ is asymptotically normal with general estimated variance matrix given by

$$\hat{\mathrm{V}}\left(\hat{\boldsymbol{\beta}}_1\right) = \hat{\mathbf{A}}^{-1}\hat{\mathbf{B}}\hat{\mathbf{A}}'^{-1}, \tag{14}$$

where $\hat{\mathbf{A}} = \sum_i \left.\dfrac{\partial \mathbf{s}_i}{\partial \boldsymbol{\beta}_1'}\right|_{\hat{\boldsymbol{\beta}}_1}$, $\hat{\mathbf{B}}$ is an estimate of $\mathrm{V}\left(\sum_i \mathbf{s}_i\right)$, and $\mathbf{s}_i = \partial \ell_i\left(\boldsymbol{\beta}_1\right) / \partial \boldsymbol{\beta}_1$.

Since all workers within an occupation are assigned the same MET value, regression errors for workers in the same occupation are likely to be correlated (a situation analogous to that encountered by Hersch 1998). Similarly, 20.9% of the sample households contribute more than one person to the sample, so that error terms of individuals living in the same household could be correlated too. Standard errors not corrected for these correlations may be too small. Hence, I control for within-cluster error correlation at the occupation and household levels using the robust variance matrix estimator proposed in Cameron et al. (2011):

$$\hat{\mathrm{V}}\left(\hat{\boldsymbol{\beta}}_1\right) = \hat{\mathrm{V}}_O\left(\hat{\boldsymbol{\beta}}_1\right) + \hat{\mathrm{V}}_H\left(\hat{\boldsymbol{\beta}}_1\right) - \hat{\mathrm{V}}_{O \cap H}\left(\hat{\boldsymbol{\beta}}_1\right). \tag{15}$$

The three components $\hat{\mathrm{V}}_O$, $\hat{\mathrm{V}}_H$, and $\hat{\mathrm{V}}_{O \cap H}$ are separately calculated by estimating probit models with variance matrix estimates based, respectively, on clustering on occupation, clustering on household, and clustering on the interaction between occupation and household. The central matrices of $\hat{\mathrm{V}}_O$, $\hat{\mathrm{V}}_H$, and $\hat{\mathrm{V}}_{O \cap H}$ are calculated using the standard formula for one-way clustering. For example, in the case of clustering by occupation

$$\hat{\mathbf{B}}_O = \sum_{g=1}^{197} \hat{\mathbf{s}}_g \hat{\mathbf{s}}_g', \tag{16}$$

where $\hat{\mathbf{s}}_g = \sum_{i=1}^{N_g} \hat{\mathbf{s}}_{ig}$ and g denotes the gth of 197 clusters.[9]

Besides the worker's occupational MET value, included in $\mathbf{x}_{1i}$ are control variables for possible sources of on-the-job, circadian, and commuting disutility: Hours worked in the observation day (net of work breaks), job start hour, travel-to-work time (a proxy for the disutility of commuting), sector of employment (private or public), age, sex, 2 educational attainment dummies, indicators for the presence of a spouse/partner in the household and of children aged 0-2 and 3-5, the number of other adults beyond the spouse/partner, a disability indicator, and 17 region dummies. Furthermore, unobserved industry and occupation characteristics could be correlated with the MET value, whereby 12 major industry and 8 major occupation dummies are also included in $\mathbf{x}_{1i}$.[10] Descriptive statistics of these and other variables used in this study are presented in Table 3.

Letting $\mathbf{x}_{1i(j)}$ represent the vector $\mathbf{x}_{1i}$ with the jth regressor dropped, the partial effect of x_{1ij} on $P\left(y_{1i}=1 \middle| \mathbf{x}_{1i}\right)$ is $\Phi\left(\mathbf{x}'_{1i(j)}\boldsymbol{\beta}_{1(j)} + \beta_{1j}\right) - \Phi\left(\mathbf{x}'_{1i(j)}\boldsymbol{\beta}_{1(j)}\right)$ if x_{1ij} is binary, and $\phi\left(\mathbf{x}'_{1i}\boldsymbol{\beta}_1\right)\beta_{1j}$ if x_{1ij} is continuous, $\phi(\cdot)$ being the standard normal density. Average partial effects (APEs) are estimated by plugging in $\hat{\boldsymbol{\beta}}_1$ and then averaging across observations, with standard errors calculated using the delta method. The presence of clustering does not invalidate probit APEs provided that the cluster variable is independent of $\mathbf{x}_{1i}$ (Wooldridge 2010, p. 584).

9 The variance matrix estimator (15) relies on asymptotics that are in the number of occupations, which is the grouping dimension with the fewest number of clusters (Cameron and Miller 2015). Stata uses by default $\sqrt{c}\hat{\mathbf{s}}_g$ in (16) rather than $\hat{\mathbf{s}}_g$, with $c = 197/(197-1)$, to reduce downward bias in $\hat{\mathrm{V}}_O$ due to finite occupations, and applies analogous small-sample corrections at household and occupation-household levels. Although the number of available occupations seems sufficiently large so as to base inference on standard normal and chi-squared critical values, the small-sample modifications implemented by Stata are preserved.

10 These dummies are at the level of broad groups of the 1993 Spanish National Classification of Economic Activities and of the CNO-94, respectively. Broad groups comprising less than 1% of the sample were merged with adjacent groups.

TABLE 3—SAMPLE DESCRIPTIVE STATISTICS

Variable (minutes per day)	Mean	S.D.	Min	Max	% = 0
Main break non-working	70.7	61.6	0	300	22.0
Main break resting	38.4	31.9	0	160	22.2
Other (shorter) breaks non-working	6.8	14.1	0	110	76.1
Other (shorter) breaks resting	7.9	14.3	0	70	71.3
Working time (net of breaks)	492.4	74.6	370	740	
Travel-to-work time	25.6	15.6	0	90	1.6
Variable	Mean	S.D.	Min	Max	
MET value	2.74	1.23	1.50	7.50	
Job start hour (6 – 15)	8.2	1.7	6	15	
Age (in years)	38.6	11.1	18	64	
No. of other adults (beyond spouse/part.)	1.2	1.4	0	8	

Variable (%)	Mean	*Variable (%)*	Mean
Split workday	52.6	Presence of children [0-2]	7.8
Private sector	79.4	Presence of children [3-5]	9.2
Manager	2.3	Disabled	9.2
Technician/Professional	10.3	Andalucía	17.8
Supporting technician/prof.	15.6	Aragón	2.7
Clerical worker	10.0	Principado de Asturias	2.7
Service/Sales worker (incl. military)	15.0	Islas Baleares	2.4
Agricultural worker	1.2	Canarias	4.3
Manufacturing worker	22.3	Cantabria	3.1
Operator	10.0	Castilla y León	4.1
Unskilled worker	13.4	Castilla-La Mancha	3.8
Agriculture/Extraction	3.6	Cataluña	18.1
Manufacturing/Utilities	23.3	Comunidad Valenciana	6.4
Construction	13.9	Extremadura	1.8
Trade	15.8	Galicia	8.0
Hotel industry	4.0	Comunidad de Madrid	10.2
Transport	5.1	Región de Murcia	2.9
Financial intermediation	3.8	Comunidad Foral de Navarra	4.9
Real state	7.1	País Vasco	2.8
Public administration	9.5	La Rioja	2.3
Educational services	3.0	Ceuta y Melilla	1.9
Health services	6.6	Monday	17.8
Community/Personal services	3.0	Tuesday	18.4
Private households	1.4	Wednesday	17.4
Male	64.2	Thursday	17.7
Less than high school graduate	46.0	Friday	22.2
High school graduate	34.5	Saturday	4.6
University degree	19.6	Sunday	1.9
Spouse/Partner present	63.6		

Notes: Data pertain to 5773 full-time employees observed in a regular working day.
Source: Spanish Time Use Survey, 2002-2003, INE.

4.2 Main Break

The main break is analyzed using a standard Tobit model. Let y_{2i}^{*}, a continuous random variable with

$$y_{2i}^{*} = \mathbf{x}_{2i}'\boldsymbol{\beta}_2 + u_{2i}, \qquad (17)$$

represent worker i's propensity to take a mid-workday break, where $\mathbf{x}_{2i}$ is a vector of explanatory variables, $\boldsymbol{\beta}_2$ is an unknown parameter vector, and u_{2i} represents a zero-mean normally distributed random error with $Var\left(u_{2i}\right) = \sigma^2$. The observed duration of the break is positive when y_{2i}^{*} exceeds 0; in this case, the observed duration equals the propensity to take the break. When this propensity is negative, the observed duration is 0. Actual duration can thus be represented as

$$y_{2i} = \max\left(0, y_{2i}^{*}\right). \qquad (18)$$

Since the empirical definitions of y_{2i} include any time spent resting/non-working between two working spells of the same workday, it is expected that y_{2i}^{*} be influenced by the type of workday (y_{1i}), for the split workday allows a longer mid-workday break than the straight one. However, it should be noted that y_{1i} is not included in $\mathbf{x}_{2i}$ in order to be able to estimate the total effect of physical work intensity. This variable is expected to exert both a direct effect on y_{2i} (i.e. an effect holding the type of workday fixed), plus an indirect effect through its hypothesized positive influence on $P\left(y_{1i} = 1 \middle| \mathbf{x}_{1i}\right)$. Hence, if y_{1i} were included in $\mathbf{x}_{2i}$, only the direct effect would be being evaluated. Equation (17) is therefore a reduced-form model.

The exclusion of y_{1i} from $\mathbf{x}_{2i}$ suggests that u_{1i} and u_{2i} are (positively) correlated. Thus, an estimator that modeled this correlation would be more efficient than conducting separate probit and Tobit estimations. However, the analysis in Stapleton and Young (1984) suggests that the presence of measurement error in y_{2i} would be transmitted to the joint estimator of $\boldsymbol{\beta}_2$ and $\boldsymbol{\beta}_1$. There is some reason to think that at least the observations with $y_{2i} = 0$ may contain error. In Spain, the length of rest time is regulated by a national law, the Statute of workers' rights, whose art. 34.4 entitles adults who work for more than 6 hours at a stretch to a break of at least 15 minutes. However, 22.0% of the sample (respectively, 22.2%) report no time spent non-working (resting), which may be in part due to the underreporting of socially undesirable behaviors or of very short activities (Robinson 1985). To guard against the possible consequences of measurement error, separate probit and Tobit models are estimated. Furthermore, a linear model for y_{2i} will be also estimated by OLS, as measurement error in the explaining variable is of less concern when the estimating model is linear (see, e.g., Stewart 2013).

Letting $\boldsymbol{\theta} \equiv \left(\boldsymbol{\beta}_2', \sigma^2\right)'$ denote the complete vector of parameters, the Tobit estimate $\hat{\boldsymbol{\theta}}$ is obtained by maximizing $\sum_{i=1}^{N} \ell_i\left(\boldsymbol{\theta}\right)$, where, apart from an inessential constant,

$$\ell_i\left(\boldsymbol{\theta}\right) = 1\left[y_{2i} = 0\right] \log\left[1 - \Phi\left(\mathbf{x}_{2i}'\boldsymbol{\beta}_2/\sigma\right)\right] - 1\left[y_{2i} > 0\right]\left\{\left(y_{2i} - \mathbf{x}_{2i}'\boldsymbol{\beta}_2\right)^2 \big/ 2\sigma^2 + \log\left(\sigma^2\right)\big/2\right\} \quad (19)$$

(Wooldridge 2010, p. 676). Under standard assumptions, $\hat{\boldsymbol{\theta}}$ is asymptotically normal with general estimated variance matrix given by (14), with $\hat{\mathbf{A}} = \sum_i \left.\frac{\partial \mathbf{s}_i}{\partial \boldsymbol{\theta}'}\right|_{\hat{\boldsymbol{\theta}}}$ and $\mathbf{s}_i = \partial \ell_i\left(\boldsymbol{\theta}\right) / \partial \boldsymbol{\theta}$. The two-way cluster-robust variance matrix estimate of Cameron et al. (2011) is also utilized here, which is calculated analogously to the probit case.

$\mathbf{x}_{2i}$ is composed of the same regressors used to model the type of workday, plus a complete set of dummies for day of week to allow for possible day-of-week effects in the length of the main break. Interest centers on the conditional expectation of y_{2i}, which is given by

$$E\left(y_{2i} \middle| \mathbf{x}_{2i}\right) = \Phi\left(\mathbf{x}_{2i}'\boldsymbol{\beta}_2/\sigma\right)\mathbf{x}_{2i}'\boldsymbol{\beta}_2 + \sigma\phi\left(\mathbf{x}_{2i}'\boldsymbol{\beta}_2/\sigma\right). \quad (20)$$

Defining $w_{i1} = \mathbf{x}_{2i(j)}'\boldsymbol{\beta}_{2(j)} + \beta_{2j}$ and $w_{i0} = \mathbf{x}_{2i(j)}'\boldsymbol{\beta}_{2(j)}$, the partial effect of the jth regressor on $E\left(y_{2i} \middle| \mathbf{x}_{2i}\right)$ is given by $\left[\Phi\left(w_{i1}/\sigma\right)w_{i1} + \sigma\phi\left(w_{i1}/\sigma\right)\right] - \left[\Phi\left(w_{i0}/\sigma\right)w_{i0} + \sigma\phi\left(w_{i0}/\sigma\right)\right]$ if x_{2ij} is binary, and $\Phi\left(\mathbf{x}_{2i}'\boldsymbol{\beta}_2/\sigma\right)\beta_{2j}$ if x_{2ij} is continuous. APEs are calculated as explained for the probit case, and are not invalidated either by clustering independent of the explanatory variables (Wooldridge 2010, p. 680).

5. EMPIRICAL RESULTS

Table 4 presents marginal effects in the equations for the type of workday and for the length of the mid-workday break. In column 1, probit effects for the probability of working split shifts are shown, whereas columns 2 and 3 report Tobit effects for the length of the main breaks spent non-working and resting, respectively. These models were re-estimated excluding workers whose STUS occupation comprised some Primary Group with no obvious OCS equivalent. (For brevity, the surviving workers are referred hereafter as the subsample.) Table A.1 in the Appendix, which is constructed analogously to Table 4, presents these results.

TABLE 4—SINGLE-EQUATION ESTIMATES OF TYPE OF WORKDAY AND OF LENGTH OF THE MAIN BREAK (MARGINAL EFFECTS).

Dependent variables: Probit: dummy variable = 1 for split workday, = 0 for straight workday. Tobit[a]: minutes spent on the main break non-working. Tobit[b]: minutes spent on the main break resting

	(1) Probit		(2) Tobit[a]		(3) Tobit[b]	
Explanatory variables	M.E.	S.E.	M.E.	S.E.	M.E.	S.E.
MET value	.017**	.009	.4	1.2	1.4***	.4
Hours worked (net of breaks)	.106***	.006	12.0***	1.0	7.4***	.4
Job start hour (6 - 15)	.014***	.004	1.1	.8	-.2	.3
Travel-to-work time (10 min.)	-.023***	.005	-1.9***	.4	1.1***	.3
Private sector	.220***	.030	22.8***	3.6	8.8***	1.9
Manager	.104**	.053	11.4*	5.9	8.8***	2.1
Technician/Professional	.065	.043	2.9	5.9	2.1	2.1
Supporting technician/prof.	.091***	.035	5.7	5.0	4.5***	1.5
Service/Sales worker (incl. military)	-.012	.038	.6	8.1	-4.1*	2.3
Agricultural worker	-.054	.058	-8.7	6.9	-.7	2.8
Manufacturing worker	-.053	.039	-12.7**	5.5	-5.1***	1.7
Operator	-.148***	.038	-23.6***	5.0	-8.6***	2.4
Unskilled worker	-.108**	.046	-16.2***	6.2	-6.9***	1.9
Agriculture/Extraction	.022	.028	7.4	6.1	9.1***	2.9
Construction	.142***	.025	11.8***	3.0	9.6***	1.3
Trade	.134***	.022	35.0***	4.6	11.4***	1.6
Hotel industry	-.158***	.042	-5.0	5.8	6.9**	2.9
Transport	.026	.031	11.3**	5.0	5.7**	2.7
Financial intermediation	-.177***	.029	-7.6*	4.4	.2	2.5
Real state	.107***	.028	17.6***	4.3	8.4***	2.0
Public administration	-.070**	.032	-5.3	5.9	.3	2.9
Educational services	.098**	.043	34.3***	6.8	12.8***	2.5
Health services	-.164***	.045	-17.8***	6.3	-5.7**	2.7
Community/Personal services	.080**	.037	22.6***	5.9	9.6***	2.8
Private households	.031	.046	16.6*	9.6	2.1	4.0
Age	-.001	.001	-.1	.1	.0	.0
Male	.009	.018	-4.7	2.9	3.0***	1.1
High school graduate	-.045***	.014	-6.1***	1.7	-3.6***	1.0
University degree	-.040*	.022	-5.1**	2.2	-4.2***	1.2
Spouse/Partner present	-.030*	.016	-3.7**	1.8	-3.5***	.9
No. of other adults	-.003	.006	-.7	.7	.0	.3
Presence of children [0-2]	-.012	.025	-1.0	3.1	-.6	1.5
Presence of children [3-5]	-.011	.023	-7.1***	2.4	-3.1***	1.2
Disabled	-.027	.022	-4.9**	2.0	-2.4*	1.4
Andalucía	-.016	.042	-1.9	5.5	1.8	2.8
Principado de Asturias	.026	.050	-6.0	6.1	-1.2	3.4
Islas Baleares	.047	.053	7.8	7.7	7.5**	3.8
Canarias	-.022	.047	-1.4	6.0	-1.1	3.1

Cantabria	-.005	.050	-14.1**	6.7	-4.7	3.4
Castilla y León	.114***	.037	13.3**	5.7	5.6*	3.2
Castilla-La Mancha	.089**	.042	11.2*	6.1	7.9**	3.6
Cataluña	.116***	.036	-.6	4.8	3.8	2.7
Comunidad Valenciana	.116***	.041	8.5	6.3	8.3**	3.3
Extremadura	.070	.052	4.4	7.1	5.7	4.2
Galicia	.115***	.041	4.4	5.8	3.3	3.2
Comunidad de Madrid	.067	.043	-15.0***	5.2	-.7	2.9
Región de Murcia	.078	.049	9.7	7.4	6.6*	3.7
Comunidad Foral de Navarra	-.006	.044	-4.3	6.0	-.6	3.7
País Vasco	.099**	.041	-8.4	6.1	-3.8	3.1
La Rioja	.109**	.051	5.1	8.4	3.9	4.3
Ceuta y Melilla	.052	.049	10.8	11.1	3.1	4.9
Tuesday			3.0	2.3	1.1	1.2
Wednesday			.1	2.3	-.1	1.4
Thursday			-.0	2.4	-.5	1.1
Friday			-3.8*	2.1	-2.6**	1.3
Saturday			-13.9***	4.1	-4.1**	2.1
Sunday			-29.4***	4.1	-13.6***	2.7
Log-likelihood value	-3062.0		-26,309.5		-23,445.5	
R-squared	.233		.241		.200	
$\hat{\sigma}$	–		64.7		34.6	
Observations	5773		5773		5773	

Notes: The table shows results for the complete sample of full-time employees observed in a regular working day. All estimations include an intercept. Standard errors are clustered at the occupation and household levels, and are calculated with the delta method. *R*-squared for the probit model equals one minus the ratio of the log likelihood of the fitted function to the log likelihood of a function with only an intercept; for the Tobit model it is the squared correlation between the actual outcomes and fitted values obtained from equation (20). Unreported categories: Clerical worker, manufacturing/utilities industry, less than high school graduate, Aragón. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.
Source: Spanish Time Use Survey, 2002-2003, INE.

In the full sample, results showed that both the amount of hours worked and the job start hour are positively related to the probability of having a split workday and highly statistically significant. These relationships were expected given that, on average, split-shifters provide significantly more overtime and wake up later than comparable straight-shifters (González Chapela 2015). The probability of working split shifts is predicted to fall by .023 if the commute duration increased by 10 minutes. This effect, which achieves statistical significance at 1%, indicates that split-shifters tend to live closer to the workplace than comparable straight-shifters, and is in line with the theoretical hypothesis that the disutility of commuting is larger for the former group. The dummy variable for whether the individual works in the private sector appeared to be positive and strongly significant: Holding other factors fixed, working in the private sector increases the likelihood of working split shifts by around

42% on average. Other significant effects were evident among the occupation, industry, and region categories.

A 1 MET increase in occupational energy expenditure is predicted to increase the probability of working split shifts by .017. This effect is statistically different from zero at 5% and amounts to a 3.2% increase in the average incidence of the split workday. The effect however is larger in the subsample, where the MET value is probably measured more precisely (Yatchew and Griliches 1985): Holding other factors fixed, a 1 MET increase is predicted to rise the likelihood of working split shifts by .025, a 4.8% increase in the average incidence of the split workday. In any case, the positive sign and statistical significance of the MET value support the main claim of this paper: That the higher the physical work intensity the higher the likelihood of working under a split schedule. Thus, for example, construction laborers (MET = 6.00) are .067 to .088 more likely than otherwise comparable assistant professors (MET = 2.50) to work split shifts as a consequence of their larger physical activity.

As for the main break, estimates, as a rule, were measured more precisely when the narrowest definition of mid-workday break was used. In a regular working day, an extra hour of work is predicted to extend the main break spent non-working by 12.0 minutes, 7.4 minutes in the case of the main break spent resting. These effects are precisely measured and attain statistical significance at 1%. A 10-minute increase in the commute shortened the main break spent non-working by about 2 minutes; in contrast, the main break spent resting was extended 1.1 minute for the same reason. Independently of the measure used, the main break was found to be larger in the private sector, which agrees with the fact that the split workday is more prevalent there. The main break appeared to be shorter on Fridays, Saturdays, and, especially, Sundays.

The effect of occupational energy expenditure on the main break spent non-working was positive but very small: In a regular working day, a 1 MET increase is predicted to extend this break by 0.4 minutes in the full sample (*S.E.* = 1.2), and 1.0 minutes in the subsample (*S.E.* = 1.2). As for the main break spent resting, the effect is larger and highly significant: The same increase is predicted to extend this break by 1.4 minutes in the full sample (*S.E.* = .4), and 1.7 minutes in the subsample (*S.E.* = .4). While the sign and statistical significance of this result are consistent with the positive association between physical work intensity and the split workday, its size however may not be so large so as to demand the existence of different types of workdays. For example, according to these estimates construction laborers' superior physical work intensity is predicted to extend their main break spent resting by 5 to 6 minutes with respect to that of otherwise comparable assistant professors, which represents an increase of 13 to 16% in the average duration of that break. But construction laborers' main break spent non-working is just 1.4 to 3.5 minutes longer, which suggests that they spend less time than assistant professors during that break on other effortful tasks such as running errands or household chores.

The length of the main break was also analyzed using a linear model estimated by OLS. In this case, the two-way clustering by occupation and household was implemented using the Stata user-written command *cgmreg* (Cameron and Miller 2015). Effects derived from the linear model are shown in Table A.2 in the Appendix. Differences with respect to the Tobit case appeared to be small.

As was pointed out at the end of Section 2, the propensities to work split shifts and to take a mid-workday break may be inversely related to the total time spent on breaks other than the longest. (For brevity, I will call these other breaks short breaks spent resting/non-working.) If this were so, plus if (as intuition and some evidence suggest[11]) physical work intensity and time spent on short breaks were positively related, the omission of the latter from $\mathbf{x}_{1i}$ and $\mathbf{x}_{2i}$ would be probably biasing the coefficient associated to the MET value in the negative direction.[12] On the other hand, its inclusion in $\mathbf{x}_{1i}$ and $\mathbf{x}_{2i}$ could also be problematic. To see this, Table 5 presents the main results of re-estimating the models for y_{1i} and y_{2i} with time spent on short breaks included among the explanatory variables. (Table A.3 in the Appendix presents the results for the subsample.) In columns 1 and 3 the measure of short breaks is time spent non-working, whereas in columns 2 and 4 it is time spent resting. Independently of the measure used, both the propensity to work split shifts and the length of the main break increased with time spent on shorter breaks, which seems very counterintuitive. As for the effects of occupational energy expenditure, these showed a slight tendency in the negative direction with respect to those in

[11] An OLS regression of total time spent on short breaks on $\mathbf{x}_{2i}$ yielded a positive and statistically different from zero coefficient associated to the MET value: In a regular working day, a 1 MET increase is predicted to increase time spent on short breaks by approximately 1 minute.

[12] The direction of the biases discussed in this paragraph were derived treating y^*_{1i} and y^*_{2i} as if they were observable, and assuming that no extra explanatory variables were present.

Table 4. I believe these results could be driven by an unobserved workers' trait such as lack of stamina, because if that trait were positively correlated with y^*_{1i}, y^*_{2i}, and with time spent on short breaks, the coefficient associated to the latter would be biased in the positive direction, and that associated to the MET value would be biased in the negative direction. Consistent estimation of the models for y_{1i} and y_{2i} would require an instrumental variable for time spent on short breaks, which I was unable to find.

TABLE 5— SINGLE-EQUATION ESTIMATES OF TYPE OF WORKDAY AND OF LENGTH OF THE MAIN BREAK (SELECTED MARGINAL EFFECTS).

Dependent variables: Probit: dummy variable = 1 for split workday, = 0 for straight workday. Tobit[a]: minutes spent on the main break non-working. Tobit[b]: minutes spent on the main break resting

	(1) Probit		(2) Probit		(3) Tobit[a]		(4) Tobit[b]	
Explanatory variables	M.E.	S.E.	M.E.	S.E.	M.E.	S.E.	M.E.	S.E.
Short breaks non-working (10 min.)	.035***	.005	–		6.9***	.6	–	
Short breaks resting (10 min.)	–		.053***	.005	–		4.9***	.3
MET value	.014*	.008	.013	.008	-.2	1.2	1.1***	.4
Hours worked (net of breaks)	.100***	.006	.096***	.006	11.1***	.9	6.9***	.4
Job start hour (6 - 15)	.015***	.004	.015***	.004	1.3*	.8	-.1	.3
Travel-to-work time (10 min.)	-.024***	.005	-.022***	.005	-2.1***	.4	1.2***	.3
Private sector	.211***	.030	.202***	.030	21.2***	3.5	7.2***	1.8
Log-likelihood value	-3025.3		-2974.9		-26,216.5		-23,276.6	
R-squared	.243		.255		.259		.239	
$\hat{\sigma}$	–		–		63.7		33.6	
Observations	5773		5773		5773		5773	

Notes: The table shows results for the complete sample of full-time employees observed in a regular working day. All estimations include an intercept plus age, sex, 2 educational attainment dummies, indicators for the presence of a spouse/partner in the household and of children aged 0-2 and 3-5, the number of other adults beyond the spouse/partner, a disability indicator, 17 region dummies, 12 major industry dummies, and 8 major occupation dummies. Furthermore, estimations (3) and (4) include a complete set of day of week dummies. Standard errors are clustered at the occupation and household levels, and are calculated with the delta method. *R*-squared for the probit model equals one minus the ratio of the log likelihood of the fitted function to the log likelihood of a function with only an intercept; for the Tobit model it is the squared correlation between the actual outcomes and fitted values obtained from equation (20). *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.
Source: Spanish Time Use Survey, 2002-2003, INE.

6. CONCLUSION

This paper has shown that the existence of occupational variations in physical job requirements can generate differences in workers' type of workday (split or straight). The crucial assumption to establish this link is that the degree of recovery allowed by the mid-workday break be influenced by the physical load of the work done. If the reduction in fatigue achieved per unit of time resting/non-working is larger (respectively, smaller) the larger is the physical work intensity, then the probability of working split shifts will increase (decrease) in the physical load of the work done, ceteris paribus. The theoretical model also identified other factors that can give rise to differences in workers' type of workday, such as the disutility derived from commuting and from circadian rhythms created by physiological and possibly psychological and social temporal patterns. These factors can be relevant to explain cross-country differences in the prevalence of the split workday.

The paper has also explored empirically the linkage between physical work intensity and the type of workday by approximating the former with an occupational average of energy expenditure. The results indicate that physical work intensity is positively associated to the probability of working split shifts. The magnitude of this effect is such that construction laborers' higher physical work intensity would make them .067 to .088 more likely than otherwise comparable assistant professors to work split shifts, which represents an increase of approximately 13 to 17% in the average incidence of the split workday. In agreement with the estimates for the type of workday, estimates based on the length on the work breaks taken also reveal evidence of a positive effect of physical work intensity on the duration of the main break. The order of magnitude of this effect is similar to that observed for the type of workday in the case of time spent resting, but is smaller for time spent non-working, which suggests that individuals working in occupations that require more physical activity tend to reduce other effortful tasks during the main break.

APPENDIX

TABLE A.1—SINGLE-EQUATION ESTIMATES OF TYPE OF WORKDAY AND OF LENGTH OF THE MAIN BREAK (MARGINAL EFFECTS). OCCUPATIONS WITHOUT OBVIOUS OCS EQUIVALENTS EXCLUDED

Dependent variables: Probit: dummy variable = 1 for split workday, = 0 for straight workday. Tobit[a]: minutes spent on the main break non-working. Tobit[b]: minutes spent on the main break resting

	(1) Probit		(2) Tobit[a]		(3) Tobit[b]	
Explanatory variables	M.E.	S.E.	M.E.	S.E.	M.E.	S.E.
MET value	.025***	.009	1.0	1.2	1.7***	.4
Hours worked (net of breaks)	.103***	.008	11.4***	1.1	7.1***	.5
Job start hour (6 - 15)	.016***	.005	1.5	1.0	.1	.4
Travel-to-work time (10 min.)	-.020***	.005	-1.7***	.4	1.2***	.3
Private sector	.218***	.035	24.4***	4.1	9.0***	2.2
Manager	.049	.049	13.7	8.7	7.9***	3.0
Technician/Professional	.059	.047	4.2	6.6	1.6	2.3
Supporting technician/prof.	.101***	.033	6.8	5.7	4.7***	1.5
Service/Sales worker (incl. military)	-.033	.042	.6	8.4	-4.4*	2.3
Agricultural worker	-.106*	.056	-12.1	7.4	-1.6	2.9
Manufacturing worker	-.081**	.040	-15.8***	5.8	-5.2***	1.8
Operator	-.135***	.043	-23.6***	5.7	-7.3**	3.0
Unskilled worker	-.148***	.044	-20.6***	6.4	-8.3***	1.9
Agriculture/Extraction	.038	.027	8.9	6.7	9.7***	3.0
Construction	.125***	.025	11.1***	3.5	8.8***	1.5
Trade	.121***	.024	33.5***	4.8	11.1***	1.6
Hotel industry	-.167***	.042	-7.5	5.4	6.2**	2.8
Transport	.014	.031	11.6**	5.6	5.6*	3.0
Financial intermediation	-.186***	.026	-10.7**	4.2	.5	2.5
Real state	.084***	.031	15.5***	4.8	7.0***	2.1
Public administration	-.094***	.034	-7.1	6.4	-.8	3.2
Educational services	.078*	.043	34.8***	7.7	12.2***	2.8
Health services	-.223***	.047	-23.4***	6.5	-9.1***	2.7
Community/Personal services	.053	.048	21.0***	6.4	8.5***	2.8
Private households	.004	.046	9.4	7.5	-1.5	1.8
Age	-.001	.001	-.0	.1	.0	.0
Male	-.001	.017	-3.9	3.2	3.0**	1.2
High school graduate	-.044***	.016	-5.6***	1.9	-3.3***	1.0
University degree	-.049**	.023	-5.5**	2.5	-4.1***	1.2
Spouse/Partner present	-.033*	.018	-3.8*	2.0	-3.3***	1.0
No. of other adults	-.004	.006	-.3	.7	.1	.3
Presence of children [0-2]	-.028	.028	-3.1	3.4	-.7	1.7
Presence of children [3-5]	-.009	.026	-6.9***	2.5	-3.5**	1.4
Disabled	-.027	.025	-5.3**	2.3	-2.6	1.6
Andalucía	-.028	.045	-1.6	5.7	1.4	3.1
Principado de Asturias	.073	.050	-.5	6.1	.8	3.7
Islas Baleares	.015	.054	7.2	8.3	6.2	4.2
Canarias	-.030	.053	-4.2	6.0	-2.7	3.2
Cantabria	-.024	.053	-17.3**	6.8	-6.1*	3.5
Castilla y León	.111***	.039	13.5**	5.7	5.6	3.4
Castilla-La Mancha	.085*	.045	12.4**	6.0	7.1**	3.5
Cataluña	.112***	.039	.9	4.9	4.1	3.0
Comunidad Valenciana	.101**	.044	5.7	6.4	7.8**	3.6
Extremadura	.066	.057	3.9	7.2	5.4	4.5

Galicia	.132***	.044	7.3	6.2	4.2	3.5
Comunidad de Madrid	.053	.046	-16.5***	5.3	-1.3	3.2
Región de Murcia	.059	.053	8.0	8.0	6.4	4.1
Comunidad Foral de Navarra	.018	.045	-2.6	6.3	.6	4.2
País Vasco	.115***	.043	-7.4	6.0	-4.8	3.0
La Rioja	.080	.058	4.5	9.2	2.5	4.6
Ceuta y Melilla	.064	.054	19.8**	10.1	5.5	5.0
Tuesday			1.0	2.3	.3	1.3
Wednesday			-1.0	2.4	-1.1	1.6
Thursday			-.3	2.6	-.2	1.1
Friday			-4.1*	2.4	-2.6*	1.4
Saturday			-13.0***	4.6	-3.5	2.3
Sunday			-27.4***	4.0	-12.3***	2.8
Log-likelihood value	-2469.1		-21,657.6		-19,288.6	
R-squared	.245		.260		.210	
$\hat{\sigma}$	–		63.6		34.0	
Observations	4727		4727		4727	

Notes: The table shows results for full-time employees observed in a regular working day. All estimations include an intercept. Standard errors are clustered at the occupation and household levels, and are calculated with the delta method. *R*-squared for the probit model equals one minus the ratio of the log likelihood of the fitted function to the log likelihood of a function with only an intercept; for the Tobit model it is the squared correlation between the actual outcomes and fitted values obtained from equation (20). Unreported categories: Clerical worker, manufacturing/utilities industry, less than high school graduate, Aragón. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.
Source: Spanish Time Use Survey, 2002-2003, INE.

TABLE A.2— OLS ESTIMATES OF LENGTH OF THE MAIN BREAK.
Dependent variables: Linear[a]: Minutes spent on the main break non-working. Linear[b]: Minutes spent on the main break resting

	Full sample				Occupations without obvious OCS equivalents excluded			
	(1)		(2)		(3)		(4)	
	Linear[a]		Linear[b]		Linear[a]		Linear[b]	
Explanatory variables	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
MET value	-.1	1.2	1.4***	.4	.5	1.3	1.7***	.4
Hours worked (net of breaks)	11.7***	1.1	7.3***	.5	11.0***	1.3	7.0***	.5
Job start hour (6 - 15)	1.7**	.7	.1	.3	2.1**	.9	.4	.3
Travel-to-work time (10 min.)	-2.6***	.4	1.1***	.3	-2.5***	.5	1.2***	.3
Private sector	22.5***	4.0	7.6***	1.9	23.9***	4.5	7.8***	2.2
Manager	11.1*	6.2	9.0***	2.2	14.8	9.1	8.4**	3.3
Technician/Professional	3.4	5.8	2.3	1.8	4.8	6.5	1.8	1.9
Supporting technician/prof.	5.0	5.2	4.2***	1.4	6.5	5.9	4.5***	1.5
Service/Sales worker (incl. military)	4.4	8.3	-2.9	1.9	4.7	8.7	-3.1	2.1
Agricultural worker	-9.6	7.7	-.3	2.8	-12.9	8.6	-1.0	3.1
Manufacturing worker	-13.4**	6.0	-5.1***	1.6	-16.3**	6.6	-4.8***	1.8
Operator	-25.3***	5.8	-8.2***	2.5	-25.3***	6.8	-6.4**	3.1
Unskilled worker	-16.2**	7.1	-6.5***	1.8	-20.4***	7.5	-7.7***	1.9
Agriculture/Extraction	6.3	6.4	9.2***	2.9	7.9	7.0	9.8***	3.0
Construction	9.7***	2.9	9.1***	1.3	9.3***	3.4	8.4***	1.5
Trade	36.2***	4.3	11.0***	1.4	35.0***	4.7	10.9***	1.5
Hotel industry	-10.4*	6.0	5.7**	2.5	-12.9**	5.8	5.2**	2.5
Transport	11.3**	4.7	5.8**	2.6	12.0**	5.2	5.8**	2.8
Financial intermediation	-9.7**	4.6	.1	2.4	-13.1***	4.5	.7	2.4
Real state	17.9***	4.3	8.4***	2.0	16.2***	4.8	7.2***	2.1
Public administration	-5.9	5.6	.7	2.4	-7.5	6.0	-.3	2.7
Educational services	31.7***	6.6	10.9***	2.1	32.5***	7.4	10.3***	2.4
Health services	-15.4**	6.5	-3.1	2.4	-20.4***	7.0	-6.1**	2.4
Community/Personal services	22.0***	5.5	9.2***	2.4	20.4***	6.2	7.9***	2.6
Private households	18.4*	9.7	2.6	4.0	11.3	8.3	-1.0	1.8
Age	-.1	.1	.0	.0	-.0	.1	.0	.0
Male	-4.5	3.0	4.2***	1.1	-3.7	3.4	4.0***	1.1
High school graduate	-5.6***	1.7	-3.5***	.9	-5.2***	1.9	-3.3***	1.0
University degree	-4.4*	2.3	-4.3***	1.2	-4.8*	2.7	-4.1***	1.3
Spouse/Partner present	-2.2	1.8	-2.9***	.9	-2.4	2.0	-2.7***	1.0
No. of other adults	-.3	.7	.3	.3	.1	.7	.3	.3
Presence of children [0-2]	-.6	3.4	-.4	1.6	-2.9	3.6	-.4	1.7
Presence of children [3-5]	-6.8***	2.5	-2.6**	1.2	-5.9**	2.6	-2.9**	1.4
Disabled	-4.3**	2.0	-2.1	1.4	-4.9**	2.2	-2.4	1.5
Andalucía	-3.5	5.7	1.3	2.7	-3.1	5.9	.8	3.0
Principado de Asturias	-6.1	6.5	-.9	3.3	-.6	6.3	1.0	3.5
Islas Baleares	4.2	8.0	5.7	3.7	3.7	8.7	4.3	4.2
Canarias	-4.2	6.4	-2.9	3.1	-6.6	6.4	-4.3	3.4
Cantabria	-13.9*	7.5	-4.0	3.4	-17.4**	7.8	-5.3	3.6
Castilla y León	10.9*	5.6	3.7	3.0	11.2*	5.7	3.9	3.3
Castilla-La Mancha	9.5	5.8	7.0**	3.2	11.2*	5.8	6.3*	3.3
Cataluña	-2.2	5.0	3.5	2.6	-.7	5.0	3.6	2.9
Comunidad Valenciana	5.8	6.3	7.1**	3.1	3.2	6.5	6.8**	3.5
Extremadura	2.2	6.9	5.0	3.9	1.6	6.9	4.6	4.3
Galicia	2.8	6.0	2.4	3.1	5.8	6.3	3.3	3.4
Comunidad de Madrid	-18.1***	5.7	-.8	2.9	-19.5***	5.8	-1.3	3.2
Región de Murcia	7.9	7.7	5.6	3.6	6.3	8.5	5.4	4.0

Comunidad Foral de Navarra	-7.0	6.1	-1.8	3.7	-4.7	6.4	-.2	4.2
País Vasco	-9.2	6.5	-3.9	2.9	-7.9	6.3	-5.1*	3.0
La Rioja	6.9	7.9	4.8	3.8	6.5	8.7	3.4	4.1
Ceuta y Melilla	11.1	10.1	3.1	4.0	19.0**	9.6	4.6	4.4
Tuesday	2.5	2.3	.8	1.2	.7	2.4	.2	1.4
Wednesday	-.1	2.4	-.2	1.5	-1.1	2.6	-1.2	1.7
Thursday	-.1	2.6	-.6	1.1	-.4	2.8	-.2	1.1
Friday	-3.2	2.2	-2.3*	1.3	-3.6	2.6	-2.2	1.5
Saturday	-13.1***	4.5	-3.0	2.1	-12.0**	5.2	-2.3	2.3
Sunday	-27.5***	4.2	-11.7***	2.6	-25.9***	4.0	-10.6***	2.7
Intercept	-38.9***	14.0	-38.2***	5.7	-38.7**	16.9	-38.9***	6.5
R-squared	.248		.207		.265		.215	
$\hat{\sigma}$	53.6		28.5		53.2		28.3	
Observations	5773		5773		4727		4727	

Notes: The table shows results for full-time employees observed in a regular working day. Standard errors are clustered at the occupation and household levels, and are calculated with the delta method. Unreported categories: Clerical worker, manufacturing/utilities industry, less than high school graduate, Aragón. *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.
Source: Spanish Time Use Survey, 2002-2003, INE.

TABLE A.3— SINGLE-EQUATION ESTIMATES OF TYPE OF WORKDAY AND OF LENGTH OF THE MAIN BREAK (SELECTED MARGINAL EFFECTS). OCCUPATIONS WITHOUT OBVIOUS OCS EQUIVALENTS EXCLUDED

Dependent variables: Probit: dummy variable = 1 for split workday, = 0 for straight workday. Tobit[a]: minutes spent on the main break non-working. Tobit[b]: minutes spent on the main break resting

	(1)		(2)		(3)		(4)	
	Probit		Probit		Tobit[a]		Tobit[b]	
Explanatory variables	M.E.	S.E.	M.E.	S.E.	M.E.	S.E.	M.E.	S.E.
Short breaks non-working (10 min.)	.030***	.005	–		6.5***	.7	–	
Short breaks resting (10 min.)	–		.049***	.005	–		4.7***	.4
MET value	.022***	.008	.020***	.008	.4	1.2	1.4***	.4
Hours worked (net of breaks)	.098***	.008	.094***	.007	10.6***	1.0	6.6***	.4
Job start hour (6 - 15)	.017***	.005	.017***	.005	1.7*	1.0	.2	.4
Travel-to-work time (10 min.)	-.021***	.005	-.020***	.005	-2.0***	.5	1.3***	.3
Private sector	.208***	.035	.199***	.035	22.7***	4.0	7.4***	2.1
Log-likelihood value	-2446.5		-2406.2		-21,589.6		-19,160.4	
R-squared	.252		.264		.275		.246	
$\hat{\sigma}$	–		–		62.7		33.1	
Observations	4727		4727		4727		4727	

Notes: The table shows results for full-time employees observed in a regular working day. All estimations include an intercept plus age, sex, 2 educational attainment dummies, indicators for the presence of a spouse/partner in the household and of children aged 0-2 and 3-5, the number of other adults beyond the spouse/partner, a disability indicator, 17 region dummies, 12 major industry dummies, and 8 major occupation dummies. Furthermore, estimations (3) and (4) include a complete set of day of week dummies. Standard errors are clustered at the occupation and household levels, and are calculated with the delta method. *R*-squared for the probit model equals one minus the ratio of the log likelihood of the fitted function to the log likelihood of a function with only an intercept; for the Tobit model it is the squared correlation between the actual outcomes and fitted values obtained from equation (20). *: Significant at 10%. **: Significant at 5%. ***: Significant at 1%.
Source: Spanish Time Use Survey, 2002-2003, INE.

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