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222

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Abstract

We examine the effect of commuting on labour supply patterns. A labour supply model is introduced which shows that commuting distance increases daily workhours, whereas the effect on total labour supply is ambiguous. This paper addresses these issues empirically using the socio-economic panel data for Germany between 1997 and 2007. Endogeneity of commuting distance is accounted for by using employer-induced changes in commuting distance. In line with the theoretical model developed, we find that commuting distance has a slight positive effect on daily workhours. Further, we find a similar effect on weekly labour supply, but no effect on workdays. Distinguishing between males and females, it appears that the effects on labour supply are mainly through the behaviour of females, but the effects for females are still small.

Keywords: Commuting, congestion tax, labour supply

JEL codes: J22, R41

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1. Introduction

In the current paper, we focus on the effect of commuting on labour supply patterns, including workhours, workdays and weekly labour supply. There are a number of reasons why this topic is of interest to economists. One reason is that there are divergent theoretical views on this effect (e.g. Cogan, 1981; Parry and Bento, 2001). This is related to different assumptions regarding the relevant behavioural margins. In one literature, it is assumed that the number of workdays is chosen and the number of workhours per day is fixed, whereas in another literature, opposite assumptions are made. When examining the effect of commuting, it turns out that these assumptions generate different predictions about the relationship between labour supply and commuting.

The second reason is related to policy: there are a range of arguments (mainly congestion and agglomeration externalities) why governments use policies that tax or subsidize commuting (De Borger and van Dender, 2003; Borck and Wrede, 2008; 2009; Hymel, 2009). A relevant question is then how these policies affect labour supply patterns, which depend on the relationship between commuting and labour supply. In addition, there is a substantial literature on government regulation of housing construction (Saks, 2008). It is then important to know whether increases in commuting distance due to government regulation also have (negative) effects on labour supply.

A third reason is that it may help us to understand long-run developments in working patterns and commuting (see also Van Ommeren and Rietveld, 2005). For example, it has been well documented that the increase in the spread of workers' starting time is closely related to the phenomenon of peak congestion, mainly caused by commuters (Henderson, 1981; Wilson, 1988). Similarly, it may be thought that any increase in commuting costs (e.g. due to congestion) encourages workers to increase daily workhours and decrease number of workdays. If true, then this is another good example of how commuting causes changes in working patterns (see also Baum, 2009).

A fourth reason is that the textbook analysis of congestion pricing implies that the welfare in the economy does not depend on how the revenue of the road tax is redistributed into the economy (see e.g. Small and Verhoef, 2007, p. 120). This result is obtained under the assumption that the demand and supply of transport is not distorted by other taxes. In case of commuting however, it seems more reasonable to assume that labour supply is negatively distorted by an income tax (e.g. Bovenberg and Goulder, 1996; Parry and Bento, 2001; Mayeres and Proost, 2001; Calthrop, 2001). In this case, a road tax may even have a negative effect on welfare (Parry and Bento, 2001). One of the main consequences is that to increase welfare in the economy, the revenues of road pricing should be used to reduce the level of the distortionary income taxes (Parry and Bento, 2001). Therefore, the relevant empirical question is whether labour supply is indeed reduced by a road tax. We do not observe road taxes in most parts of the world but one may examine how an increase in commuting distance affects labour supply, which gives insight into the effect of a road tax on labour supply.

The empirical literature in economics that deals with the relationship between commuting behaviour and the workers' labour supply is closely related to the theoretical literature. Theoretical urban models essentially assume that the residence location is endogenous (e.g. Wales, 1978; White, 1988), whereas labour models assume that it is given (e.g. Gubits, 2004).[1] In the theoretical section, we keep residence location given in the spirit of labour economics models, and we consider exogenous changes in the commuting distance. In the empirical section, we deal with the endogeneity of commuting distance.

To understand the effect of exogenous changes in commuting costs on changes in labour supply, it is useful to examine the work by labour economists who focus on the optimal setting of number of workhours for workers. Although it is common that theoretical and empirical research focuses on one measure of labour supply (e.g. hours per week), only few studies have

[1] Urban models assume that commuting distance is optimally chosen based on an optimal choice of the residence taking (endogenously determined) house prices into account, so that workers are fully compensated for longer commutes by lower house prices. Static labour models usually assume that the number of workhours is optimally chosen given the commuting distance and wage.

focused on more flexible specifications of labour supply patterns (e.g. working weeks per year and working hours per week; see e.g. Hanoch, 1980, p. 119; Blank, 1988). One important issue is then the presence of fixed costs of work, such as commuting costs, which are costs that are not related to the amount of labour supplied. Cogan (1981) establishes that when fixed costs are present, the period of time over which the fixed costs are incurred is the ideal measure of labour supply. That is, if fixed costs are *per day*, such as daily commuting costs, and these daily costs are important, then the appropriate measure of labour supply is daily labour supply. Cogan (1981), as a response to the seminal paper by Heckman (1980), examines the effect of labour costs on labour supply. Although theoretically he cannot provide an answer whether this effect is positive or negative, empirically he concludes that increases in daily fixed costs of work reduce labour supply, at least for the sample of women that he analyses. Cogan (1981), and subsequently textbooks in labour economics (e.g. Ehrenberg and Smith, 2003), assume that the number of workhours is optimally chosen given the commuting distance, which implies that labour supply is optimally chosen *per day*.[2] This literature indicates that both daily workhours and total labour supply decline with an increase in commuting *time*, but increase with an increase in *monetary* commuting costs (see e.g. Manning, 2003; Gubits, 2004).

In contrast, Parry and Bento (2001) make the opposite assumption by assuming that workers optimally choose their *number of workdays*, whereas daily hours are fixed. This assumption is nowadays standard in the transport literature on labour supply and commuting (e.g. Calthrop, 2001). The number of workdays per week determines then the total commuted distance per week (the distance between the residence and the workplace times the number of workdays). Consequently, there is a strict complementarity between the commuted distance per week and total labour supply.[3] This assumption simplifies the analysis of the effect of

[2] In this literature, slightly confusingly, it is not discussed explicitly whether labour supply is per day or per week, but since commuting costs are considered *fixed*, labour supply must be per day. This literature then shows that workers optimally choose a minimum but positive number of daily hours.

[3] With strict complementarity we mean that a change in labour supply implies a proportional change in the distance travelled (e.g. per week). See also Wuyts (2009) who allows for telecommuting and therefore does not assume complementarity.

commuting costs on labour supply, but implies that, conditional on the choice of transport mode, given an increase in commuting costs workers may only adapt their commuting costs by adapting total labour supply.[4] The model implies then that commuting time *decreases* number of workdays as well as total labour supply, whereas the effect of monetary commuting costs on these variables is ambiguous. Based on assumptions regarding the size of the income and substitution effects, the authors presume that if monetary costs increase, total labour supply decreases.[5]

Arguably, workers have other behavioural margins than a reduction in labour supply to reduce their commuting costs.[6] We will discuss here three relevant behavioural margins that are discussed in the literature. First, workers have quite some flexibility with respect to the chosen workhours (see e.g. Arnott, 2005, p. 135). Particularly in congested areas, workers may leave earlier, or later, from home, in order to avoid peak hours (Arnott et al., 1993). Second, workers may change commuting costs by moving residence (Gubits, 2004). Third, and this will be the focus of the current paper, workers have the option to increase the number of hours worked *per day* and, maybe simultaneously, decrease the number of workdays. As already noted by Hamermesh (1996) for Germany, the variation in daily hours is slightly larger than the variation in days, suggesting that this mechanism is important. Hence, in a more general setting than usually assumed, the effect of an increase in commuting costs (e.g. induced by a road tax) on *total* labour supply may be negligibly small, or, as we will see, even positive.

As far as we are aware, this is the first study that distinguishes theoretically and empirically between number of workdays and daily labour supply. In the theoretical model, it is assumed that both daily hours and number of workdays (e.g. per week) are optimally chosen by

[4] Given this assumption, in order to measure the effect of commuting costs on labour supply, it is reasonable to employ empirical labour supply elasticities that are based on the estimated relationship between labour supply and wages (see e.g. Parry and Bento, 2001). If this assumption does not hold, then to employ these elasticities may be incorrect.

[5] It is then intuitive that a road tax that increases commuting costs may reduce welfare given the presence of a distortionary income tax. Recycling the road-tax revenues by reducing the levels of income tax will then increase welfare (as demonstrated by Parry and Bento, 2001)

[6] So, the revenue-recycling argument may not hold in a more general setting. This is relevant as the other behavioural margins are not, or at least not systematically, distorted by the income tax.

workers. Empirically, we observe commuting distance which is positively related to commuting time and monetary costs. It is shown that *both monetary and time commuting costs increase daily hours*. Hence, workers with longer commuting distances (and therefore longer commuting times and higher monetary costs) will unambiguously increase daily workhours. Furthermore, it is shown that commuting *time* reduces workdays, but the effect of commuting costs is ambiguous. The effect of distance on workdays is therefore ambiguous. These effects of commuting time and monetary commuting costs, and therefore distance, on total labour supply are all ambiguous, as it is not clear a priori whether the effect on daily hours or workdays dominates.

In the empirical section, we examine the effect of commuting distance on labour supply patterns, distinguishing between total labour, daily labour supply and number of workdays, where daily labour supply is defined as the number of workhours per day (in empirical studies known to us, labour supply is measured per week or even longer period, the main exception is Hamermesh, 1996). We use the socio-economic panel data for Germany between 1997 and 2007. One of the main issues we are concerned with is that commuting distance may be endogenous with respect to labour supply patterns. We use therefore a worker first-differences approach and employ an innovative approach where changes in commuting distance are employer-induced, and therefore exogenous. This approach is not only useful in the context of labour supply, but will be useful in many other applications where it is thought that distance is endogenous.

This is a relevant consideration because in the literature it is emphasized that it is difficult to find instruments for commuting distance to correct for possible endogeneity (see e.g. Manning, 2002; Gubits, 2004).

In the next section, we discuss the theoretical setting. The remainder of the paper is structured as follows: section 3 provides information on the data employed, introduces the econometric model and presents the empirical results. Section 4 concludes.

2. The Model

To explain the labour supply behaviour of employed individuals, we introduce a labour supply model including commuting.[7] Hence, we assume a standard labour supply model by allowing for commuting costs and by distinguishing between daily work time and number of workdays. For an individual who participates in the labour market there are two essential decisions to be made each period (e.g. defined by a week or a year): *(i)* how much work-time per day, H, and *(ii)* how many days, D, she would like to work. So, total labour supply per period is defined by DH. The number of days D and daily work time H are assumed to be continuous variables.[8] It is assumed that the labour supply preferred by employed individuals can also be realized. Participation in the labour market implies that $DH > 0$, so that $H > 0$ and $D > 0$. In line with the literature, we assume that commuting involves time t and induces monetary commuting costs. The monetary costs are proportional to distance k with a positive cost per kilometre c and are therefore equal to kc. In our analysis, commuting speed is exogenously given (for an analysis with endogenous speed, see for example, Van Ommeren and Fosgerau, 2009).

Suppose that workers derive utility from income Y and leisure time L, and that there are only two possible uses of time: labour and leisure. The workers' utility function v can then be written as $v = V\left(Y_0 + w(H)D - Dkc, \bar{L} - DH - Dt\right)$, where $\bar{L}$ is the worker time endowment per week (or maximum leisure time), Y_0 is non-labour income and $w(H)$ is the daily wage, which depends on the number of daily hours worked. So, $Y = Y_0 + w(H)D - Dkc$ and $L = \bar{L} - DH - Dt$. We assume that the *daily* wage is increasing and concave in H. So, $w'(H) > 0$ and $w''(H) < 0$, where $w'(H)$ denotes the marginal effect of H on the wage. Concavity of the daily wage can be justified when employers pay the worker's marginal productivity and a worker

[7] We ignore income taxes, which obviously affect the net wage, as well as road taxes, which directly affect the monetary and indirectly the time costs of commuting (through reduced congestion). Introducing these taxes, as well as government budget restrictions, is necessary for welfare analyses (Parry and Bento, 2001). In the current paper however, we are mainly concerned with the effect of changes in commuting on labour supply, so we abstract from taxation issues.

[8] If the period is a year, it is clear that the number of days is continuous. If it is a week, then the assumption that the number of days is continuous is still plausible if the worker is able to vary the number of days per week over time. For example, let us suppose that an individual prefers to work 1.2 days per week. She will work one day per week for a period of four weeks and the fifth week she will work two days.

becomes less productive the more hours she works. The utility function *v* is assumed to be twice-differentiable and concave (so, the first derivatives are positive, the second derivatives are negative and the cross-derivatives are positive). This assumption is reasonable when income and leisure are both normal goods. When $DH > 0$, then $w(H) > kc$, so participation in the labour market implies that the daily wage exceeds the daily monetary commuting costs. It is assumed that workers maximize their utility by choosing daily work time *H* and days *D*.

It can be shown that the optimally chosen daily work time is defined by (see Appendix A):

$$w'(H)\left[H+t\right]=w(H)-kc. \tag{1}$$

This expression states that the worker's marginal cost of working one day (so, the marginal opportunity cost of leisure times the loss of leisure time) is equal to the daily wage net of monetary commuting costs. Given (1), it follows that *both monetary commuting costs kc and commuting time t increase the daily work time H*, because $\partial H/\partial(kc)=-\left[w''(H)\left[H+t\right]\right]^{-1}>0$ and $\partial H/\partial t=-w'(H)^{2}\left[\left[w(H)-kc\right]w''(H)\right]^{-1}>0$. Note that (1) implies that Y_0 does not affect *H*, which is a useful property of the model because it implies that it should not be used as a control variable (and can be used as an instrument in some specifications).

In a working paper version of this paper, we elaborate further on the effects of exogenous changes in monetary commuting costs *kc* and commuting time *t* on the optimally chosen number of days *D* and total labour supply *DH* (Gutiérrez-i-Puigarnau and van Ommeren, 2009). It is shown that workers may react quite differently to an increase in monetary commuting costs than to a decrease in wages (in contrast to studies that assume that these effects are identical). We demonstrate that an increase in commuting *time* decreases *D*, whereas the effect of a change in *t* on total labour supply *DH* turns out to be ambiguous. The effect of monetary costs on *D* and *DH* are also ambiguous, because the income effect of an increase in monetary costs may, or may not, dominate the substitution effect.

Here, we focus on the case that speed is exogenously given, so a change in commuting distance implies an equivalent increase in commuting time. Hence, we assume that $t = d/s$, where speed s is given. This case allows us to understand the overall effect of distance on labour supply when workers face a constant commuting speed. The overall effect of distance on labour supply involves then effects through increases in commuting time and monetary costs. This is relevant as in our empirical analysis, we observe commuting distance, but are not able to distinguish between the effect of commuting time and monetary costs separately.

In Appendix A, it is shown that an increase in distance increases H, but the effects on D and DH are ambiguous.[9] The ambiguity on DH, as well as on D, is due to two reasons. First, any increase in monetary costs (associated with an increase in distance) has an income and a substitution effect, and it is, a priori, unclear which effect dominates. Second, as we have seen above, any increase in commuting time (associated with an increase in distance) will reduce D, so DH is ambiguous.

We are also interested in the effect of a marginal increase in commuting distance on workdays and daily work time, *keeping total labour supply DH constant*. This allows us to examine the behaviour of workers that are constrained to keep total labour supply constant. Constraints by employers, collective bargain agreements, as well as by European Union labour laws are quite common and have been well documented.[10] One view may be that these restrictions are only short-run restrictions for workers, but it is equally possible that workers see these restrictions as permanent. Conditional on DH, the theoretical result that distance increases H implies that distance decreases D.

Rather obviously, conditional on total labour supply, it is true that $H\left[\partial D/\partial k\right] + D\left[\partial H/\partial k\right] = 0$, so, $\partial \log(D)/\partial k = -\partial \log(H)/\partial k$. Hence, in the empirical application, when we control for total labour supply, it is not only convenient to use *logarithms*

[9] Note that we obtain unambiguous results of distance on daily labour supply assuming that speed is given, but the same (qualitative) results can be obtained when it is assumed that speed depends on distance and that commuting time non-negatively depends on commuting distance. Empirically, this holds as the elasticity of commuting time with respect to commuting distance is 0.5. For a full discussion, see van Ommeren and Fosgerau (2009).

[10] For example, in the Netherlands, civil servants may choose from a flexible supply pattern keeping total labour supply constant (e.g. work four days per week at nine hours per day, or work four days at eight hours and one day at four hours).

of D and H, but, given a correct specification of the model, it is arbitrary to use log H or log D as the dependent variable. We will focus on log(H), as for this variable it is easy to find a variable to instrument the endogenous explanatory variable DH.

3. Labour Supply Analysis

3.1. *The data*

Our empirical study is based on information from the German Socio-Economic Panel (GSOEP) for the years 1997−2007. The GSOEP data is a very well known dataset used by many researchers (e.g. Hamermesh, 1996; Bell and Freeman, 2001). For details of the GSOEP data, see Haisken-DeNew and Joachim (2005). For each year, we have information on commuting distance as well as on labour supply per week, and for eight out of eleven years we also have information on daily hours and workdays per week. For the years 1998, 2001 and 2003, information on daily hours and workdays per week is missing.[11] For the years 1997, 1999 and 2000, information about the commuting distance is only available if the workplace municipality differs from the residence municipality, so the exact commuting distance is unknown for workers who commute to a workplace location within the residence municipality. This is unproblematic as distances of workers who live and work in the same municipality do not vary much. Hence, for these years, we have imputed a value of 5 km for workers who live and work in the same municipality.[12]

3.2. *Selection of sample and descriptive statistics*

We focus on samples of employees aged between 20 and 60 working outside their house (in order to exclude extreme outliers, the sample is restricted to those workers who work at least two hours per day and maximally 100 per week). On average, each employee is observed three times.

[11] Note that the number of workdays is not necessary the same as the number of days the worker commutes. We have only data of number of workdays per week.
[12] A sensitivity analysis shows that the results presented later on are insensitive to the imputed value (e.g. 0 or 6 km). This makes sense as the imputation refers to only 26% of the observations, and the difference between the (unobserved) distance and the imputed distance is small (less than 10% of the mean commuting distance).

The data includes demographic information on age, gender, workplace region, net hourly wage, net household monthly earnings, household members and children. Data on elapsed residence duration and job change allow us to identify changes of residence and job, and therefore allows us to construct residence and job fixed effects for each worker.[13] Data on workhours per week refer to all hours worked, including overtime. Information on firms is limited (e.g. size, industry) and will *not* be used in our analysis, because we use job fixed effects. In our data, we have information about the number of days usually worked per week for workers for whom the number of workdays per week is fixed (so it does not change from week to week). This applies to 73% of all observations. The analyses are based on a dataset of 41,611 annual observations for 11,749 employees. Our analysis of number of days and daily hours is restricted to workers for whom the number of workdays is per week fixed. This may potentially bias the results, as we have a selected sample. Arguably, this bias can be ignored because of two reasons. First, we will make use of a workers' fixed-effects approach. Using this approach and given the assumption that the coefficient to be estimated are the same for workers' with or without flexible workweeks (while allowing for worker heterogeneity with respect to number of workdays), selectivity bias is absent. Second, even if the coefficients to be estimated differ between workers, then the bias will be (negligibly) small, as the selected sample covers the large majority of workers. For the results shown, we will treat the number of days as a continuous variable, but treating the number of days as a discrete variable (e.g. 4, 5 or 6 days) generates identical results. Worker changes in workdays are quite common. In our data, on average, each year about 10% of workers change their number of workdays.

The mean one-way daily commuting distance for all workers in the period of analysis is 15.3 km, in line with a range of other studies. Consistent with studies that show that the average commuting distance increases over time, we find that, on average, commuting distance increases 0.1 km per year. Table 1 shows descriptively the relationship between workers' changes in

[13] In a previous version of this paper, we did not control for job change (but only for employer changes). We thank an anonymous referee for the suggested improvement.

labour supply and commuting distance *when we keep residence location and job constant*, which we will later argue is the relevant measure to deal with the endogeneity of distance. For example, when the annual change in commuting distance exceeds 5 km, the average number of workdays per week decreases by 0.2% whereas the number of daily hours increases by 1.5% and weekly hours increase by 1.4%. This strongly suggests that daily and weekly labour supply increase with distance.

In Appendix B, Table B1 shows patterns of workhours per day and workdays for the years that these data are available. 85% of the workers work *exactly* five days per week, which seems clearly the 'norm'. Only 8% of the workers work more than five days and only 7% less than five days. These percentages suggest that either employers restrict the number of workdays or there is little variation in preferences of workers.[14] In contrast, there seems to be much more variation in workhours per day. For example, only 40% of all workers work exactly eight hours. This suggests that the fundamental assumption made by studies such as Parry and Bento (2001) and Calthrop (2001) that the number of workdays is optimally chosen whereas the daily hours are fixed may be less appropriate, at least for Germany. It appears also that there is large difference in the distribution of workdays and daily hours between males and females, which suggests that the effect of commuting costs on labour supply may potentially differ by gender.

The correlation coefficient between days and daily hours is 0.22 (see Table 2). The correlation between daily hours and weekly hours is positive and significant at 0.005 level, and much larger than the correlation between days and weekly hours at 0.005 level. These correlations suggest that variation in the daily hours is more important than variation in days in determining variation in weekly labour supply. These results are in line with the results of Hamermesh (1996).

[14] In Germany, labour supply has become slightly more flexible over time: the proportion of individuals working *exactly* five days has fallen over time (86% in 1997 vs. 83% in 2007). As the drop is only slight, this seems to justify our procedure to pool the data for the different years. This slight drop is in line with the observation that Germany seems to be moving towards a more flexible labour market (Hamermesh, 1996; Ostner et al., 2003).

3.3. *Econometric model*

In our empirical application we aim to investigate whether changes in commuting distance influence labour supply patterns, measured by *weekly labour supply*, *number of workdays* and *daily hours*. Let Z_{it} denote either weekly labour supply, number of workdays or daily hours for a worker i in a specific residence and with a specific job in year t, so i refers to a specific *worker-residence-job combination*. Defining worker i in this way will be useful to address endogeneity of commuting distance. Following the labour supply literature (see e.g. Borjas, 1980; Costa, 2000; Bell and Freeman, 2001), we assume a double-log labour supply specification:

$$\log Z_{it} = \alpha_0 + \alpha_1 \log k_{\mathrm{it}} + \alpha_2 X_{it} + \varepsilon_i + u_{it}, \tag{2}$$

where α_1 is the elasticity of labour supply Z_{it} with commuting distance k_{it}, the matrix X_{it} includes time-varying controls for household characteristics (e.g. children) and work characteristics (e.g. net hourly wage rate), which are assumed to be exogenous factors, u_{it} is the overall error, and ε_i is unobserved heterogeneity, which captures unobserved time-invariant characteristics that are specific to a worker-residence-job combination. For example, these characteristics may be unobserved worker-specific preferences with respect to Z (e.g. a preference for leisure time), or they may be unobserved residence-specific characteristics (e.g. residence location) or job-specific characteristics that affect Z (e.g. nurse). The particular definition of worker i implies that when a worker changes from residence i to residence i', then $\varepsilon_i \neq \varepsilon_{i'}$. The same holds for changes in jobs (also when staying with the same employer). We treat ε_i as a fixed parameter and estimate all models in terms of first-differences, that is, variables are formulated as changes from one time period to another. Taking first-differences essentially removes ε_i from expression (2) and implies that:

$$\log\left(Z_{it}\right) - \log\left(Z_{it-1}\right) = \alpha_1 \left[\log\left(k_{it}\right) - \log\left(k_{it-1}\right)\right] + \alpha_2 \left[X_{it} - X_{it-1}\right] + v_{it}, \tag{3}$$

where $v_{it} = u_{it} - u_{it-1}$. Consistent estimation of α_1 requires that the change in commuting distance, $\log(k_{it}) - \log(k_{it-1})$, is exogenous to $\log(Z_{it}) - \log(Z_{it-1})$ and therefore not related to v_{it}. This is usually not the case, since a change in the workers' commuting distance may be the result of an endogenously chosen residence or job move. However, in (3), *the change in distance may only be the result of an exogenous workplace relocation*. The latter type of relocation can be argued to be exogenous because a change in distance keeping the same job implies that the firm has moved the worker (workers are not able to move workplace location keeping the same job). In (3), only within-workers' variation in variables for *each worker given the same residence and the same job* is employed in the estimation procedure. Thus, the effect of distance on $\log(Z_{it}) - \log(Z_{it-1})$ relates purely to *changes* in commuting distance for a *given residence* and a *given job*, so that reverse causation is eliminated, and α_1 provides a consistent estimate of the effect of commuting distance on labour supply.[15] Keeping the workers' residence and job constant as we do, any *observed* change in a worker's commuting distance must be employer-induced (due to a workplace relocation while staying with the same firm) or may also be due to measurement error.

The idea to use firm relocation as a source of exogenous change in commuting distance is also exploited in Zax (1991) and Zax and Kain (1996). Firm relocations are quite common and are therefore a useful source of variation in commuting distance. For example, about 7–8% of firms in the Netherlands are each year involved in relocation decisions (Weltevreden et al., 2007). In Great Britain, in each year 0.5% of workers state that they change residence because of an employer-induced workplace move, suggesting that workplace moves are quite important, as only a (small) proportion of workers would move residence given a workplace move (National Statistics, 2002). Note that in the GSOEP survey analysed here, there is no information whether

[15] The estimation of a *worker-residence-job* first-differences model is similar to an estimation of (3) on a selective sample of workers who do not change of residence and stay with the same job. Information of workers after they have changed residence or job is then not employed, which makes the latter estimation method less efficient.

firms move. However, by keeping job and residence given, we infer that all changes in commuting distance are caused by a (exogenous) change in commuting distance as a result of a relocation of the workplace by the firm.[16]

By including residence and job fixed effects, we essentially estimate average local treatment effects for workers who face a change in their commuting distance as their employer moves their workplace location in a certain period, but who do not move job or residence during this period. Hence, strictly speaking we do not identify the average treatment effect for the whole population of workers and this effect may differ of the effect identified. The generality of our results therefore seems to depend on the effect of commuting distance on the rate of job and residence relocations and on the frequency of job and residential moves. It appears that the literature on the effect of commuting distance on residential and job mobility indicates that there is a positive effect, but this effect is rather weak (see, for example, van Ommeren et al., 1997; 1999; for a review, see van Ommeren, 2004). Furthermore, it appears that German job and residence moving rates are low (and even lower than other European countries), implying that the large majority of workers would not move job or residence within the period the workplace relocation takes place. Hence, it is plausible that the effect identified will also hold for the whole population.

Note further that measurement error in reported distance may be important in our set up.[17] In particular, it is quite common that workers report a small change in commuting distance. So, for example, one year they report 63 km and next year a distance of 62 km. The change in distance is then maybe due to measurement error. In our data, 51% of all observations (when we keep residence and job constant) indicate a change in commuting distance, but the proportion drops to 10.2% when we consider changes in distance that exceed 5 km. These changes are much less likely due to measurement error. This suggests that in our data, about 25% of changes in

[16] One objection to our identification strategy is that the observed change in commuting is maybe *not* exogenous for top managers, who may be able to shift their workplace location while keeping the same *job*. As there are only few of those workers in our sample, we can safely exclude this case.
[17] If measurement error is white noise, it implies that our results are biased towards zero and therefore conservative (so, the true values are larger in magnitude).

commuting distance are employer-induced, whereas the other changes are due to endogenous residence and job moves. Note that measurement error may be quite frequent, but the size of the error will be small relative to the average commuting distance. Since we include the logarithm of commuting distance in the analysis, the (downward) bias in our estimates is likely small. Nevertheless, it is important to keep in mind that our estimates may be conservative.

We will now discuss the specification of the wage rate that must be included as a control variable in (3) according to theory. Net hourly wage rates are calculated by dividing net monthly earnings by monthly hours. Such a calculation introduces a form of measurement error, known as 'division bias', because measurement error in hours enters both the left and right hand-sight of (3). This results in a spurious negative correlation between hours and the wage rate (Stewart and Swaffield, 1997; Lee, 2001), because overreporting of hours would lead to an underreporting of the hourly wage rate.[18] So, we calculate the wage rate using *contractual* hours instead of observed hours, because the division bias in hourly wage rates using contractual hours is substantially less than using observed hours.

Another problem with estimating the wage elasticity in (3) is, according to some studies, the endogeneity of earnings, because of uncontrolled wealth effects (e.g. the arrival of new information about the wage rate may also lead to a revision in expected lifetime wealth, which is captured by the error term v_{it}; see MaCurdy, 1981; Altonji, 1986).[19] A valid estimation of the wage elasticity, taking these two sources of endogeneity into account, is to instrument changes in the wage rate. Economic theory suggests that human capital variables, such as age, which are correlated with wage growth, are candidates to be used as instruments (e.g. Lee, 2001). We instrument the change in wage rate using age and its square.[20] These instruments are frequently used in the labour supply literature and are frequently claimed to be exogenous with respect to

[18] The importance of wage division bias has been widely documented in the labour supply literature (e.g. Borjas, 1979; Abowd and Card, 1989; Lee, 2001; French, 2004).

[19] Workers are assumed to be wage-takers in the standard theoretical framework (given competitive labour markets), and in our model the function $w(H)$ is exogenously given. Of course, if the market is not competitive this result does not hold, which may be another reason to instrument wage

[20] A non-linear specification of age is appropriate, because one expects that older individuals are less likely to receive a wage increase, but one expects this effect to decrease after a certain age.

change in labour supply (see e.g. MaCurdy, 1981; Lee, 2001).[21] As shown in Table B2, these instruments are strong.[22]

Note however that some studies argue that changes in worker preferences for labour supply are related to age, in which case age is invalid as an instrumental variable for wage rate in estimating (3). Consequently, the estimated wage elasticity is likely to be downward bias (Altonji, 1986). For our main results that focus on the effect of distance, it appears that criticism regarding the validity of the instruments is less relevant, because, as we will show later on, it that turns out not to be necessary to control for wages in estimating the commuting distance elasticity. This is in line with studies that show that the correlation between commuting distance and wages is low (e.g. Manning, 2003).

3.4. *Empirical results*

The econometric results of all models taking first-differences in line with (3) are shown in Table 3.[23] We emphasize that in this way we control for worker, residence and job-fixed effects. Since both the labour supply variable and commuting distance are in logarithmic form, the commuting distance elasticity of labour supply is given by the coefficient of the commuting distance variable.

The first three columns of Table 3 show the results for *weekly* labour supply. The effect of commuting distance on weekly labour supply is positive and statistically significant (at 5% level). The elasticity estimate is 0.009 (s.e. 0.002). This indicates, for example, that if the commuting distance increases from 20 to 40 kilometres, individuals increase labour supply by about 15 minutes per week. We consider this a small effect. Controlling for time-varying variables (columns 2 and 3) and whether wage is instrumented does not appear to be essential,

[21] Further, note that we indirectly take into account the individual's decision to participate or not in the labour market, because we take differences for each employed individual.
[22] The effect of our instruments of wage rate growth is as expected and is in line with the literature, as age has a negative effect on wage growth (see Table B2). Although according static labour supply theory as used in this paper, commuting distance should not be included as a control in the instrumentation of wage rate, job search theory indicates that, generally, the wage rate will depend positively on commuting distance (Manning, 2003).
[23] We have also estimated fixed-effects models (instead of first-differences models) and obtained similar results, but the instrumentation of the wage is more complicated in that setting, so we prefer the first-differences results.

because the estimated effect of commuting distance on weekly labour supply not controlling for any other variable (column 1) generates almost identical results.[24]

We have experimented with other specifications for commuting distance (e.g. controlling for workplace location within the municipality of residence), but results are very similar. For example, given a linear specification of distance, the point estimate is 0.0005 (s.e. 0.0001), which corresponds to an elasticity of 0.008 (evaluated at the mean commuting distance of 15.3 km). So, essentially the same results are obtained as given a logarithmic specification of distance.

Our theoretical model assumes that labour supply patterns (hours and days worked) are optimally chosen, which may not be true for every worker. For example, workers may face restrictions on hours and days worked by employers (e.g. Ilmakunnas and Pudney, 1990; Dickens and Lundberg, 1993; Stewart and Swaffield, 1997; Euwals and van Soest, 1999; for Germany see e.g. Holst and Schupp, 1998; Wolf, 1998). These studies combine information on preferred labour supply with information on observed hours to identify restrictions on hours. We therefore have also analysed the effect of commuting distance on *preferred* weekly labour supply (see Table 3). Preferred labour supply is the answer to the following question in the survey: "If you could choose your own number of working hours, taking into account that your income would change according to the number of hours, how many hours (per week) would you want to work?".[25] The effect of distance on preferred weekly labour supply is insignificant (0.003 with an s.e. of 0.003).[26] We have also estimated the effect of commuting distance on the *difference* between log preferred and log (reported) weekly labour supply. The estimate of distance on the difference between preferred and (reported) labour supply is −0.006 (s.e. 0.003), consistent with the results in Table 3. This suggests that workers react stronger to changes in commuting

[24] Other estimates are as expected: the individual's labour supply decreases with other household income, having children also brings out a negative effect on labour supply, especially by women. Our instruments in [2] are strongly correlated with the endogenous variable change in wage; for example, the Kleibergen-Paap F-statistic for instrument strength is large. As expected, if we do not instrument wage growth in [2] (so, we perform an OLS regression), the estimate of net hourly wage is biased downwards.

[25] Note that this question is slightly ambiguous for our purpose, because it may not specifically be related to the current job.

[26] For 29% of workers, preferred weekly labour supply is missing, and these observations have been excluded.

distance than they would choose without employer restrictions. This result is seemingly a paradox, but one explanation is that workers with long commutes prefer to leave later in the evening, but are not allowed by employers to arrive later in the morning (or the opposite case), hence they are 'forced' to work more hours per day.

Columns 7–14 of Table 3 show the results of commuting distance on number of workdays and daily hours. In line with the theoretical model developed (and the descriptive statistics in Table 1), we find a positive elasticity of daily hours with commuting distance (0.010 with an s.e. of 0.002). This elasticity of daily hours with commuting distance is essentially the same as the elasticity of weekly hours. Workers with long commute distances, ceteris paribus, appear to increase the total labour supply mainly by increasing their daily labour supply. The theoretical model developed offers little insight into the expected effect of commuting distance on workdays. We estimate an insignificant elasticity of workdays with commuting distance (0.001 with an s.e. of 0.002).

Column 13 of Table 3 shows the results for workdays and daily hours *controlling for weekly labour supply*. This is useful as an additional test of the theoretical model. One statistical difficulty when *controlling for weekly labour supply* is the possible endogeneity of weekly labour supply (as workers are likely heterogeneous in their preference for leisure time). We therefore instrument the worker's weekly labour supply with *other* household income, defined as the total household income minus the worker's own-labour income, (for the first step see Table B3) and show the results in column 14 of Table 3.[27] This instrument is valid using the theoretical model as discussed just after (1). We find that the estimate of commuting distance is 0.006 (s.e. 0.004), but just not significant at the 10% level.

We have also investigated whether it is useful to distinguish between *male* and *female* workers, because it seems plausible that the effect of changes in commuting distance on labour market behaviour is gender-specific (e.g. White, 1986; Singell and Lillydahl, 1986). It is

[27] According to (1), we should not use other household income as a control variable for the daily hours' specification, so it is a valid instrument. We have tested for instrument strength using the Kleibergen-Paap test; the instrument appears to be sufficiently strong.

therefore not surprising that some studies of labour supply examine only female workers (Cogan, 1981) or only male workers (Dickens and Lundberg, 1993; Stewart and Swaffield, 1997), whether other studies look at the gender differences in labour supply (Hekman, 1980). Also our descriptive statistics in Table B1 show that labour supply patterns differ strongly between males and females. We have therefore re-estimated separate models for males and females. In Table 4, the results when we do not control for wage can be found (other results are similar).

We find now that the commuting distance elasticity of weekly hours of 0.0035 (s.e. 0.0017) for male workers is much smaller than the one obtained for female workers of 0.015 (s.e. 0.003). The effects on daily labour supply are about the same. So, our estimates indicate that the effect of commuting distance on labour supply patterns is stronger for female workers.[28] Note, however, that the effect is still small for females. A doubling of commuting distance increases weekly labour supply by 25 minutes per week for females, for males only 5 minutes. This is in line with the labour supply literature where it is generally found that females are more sensitive to the level of wages (see e.g. Blau and Kahn, 2007).

3.5. *Sensitivity analysis*

We used age to instrument wage rates in Table 3. However, one may argue that age is endogenous to labour supply patters, as older people may work a different amount of hours because of lifecycle labour supply considerations. Workers between 25 and 50 years old likely do not differ much in their intensive nor extensive labour supply. We have therefore re-estimated models for this subsample of workers, but the estimate of commuting distance remains the same**.** We have also re-estimated models excluding observations that most likely refer to measurement error in the commuting distance (changes less than 2 km), but the results remain robust.

[28] These results indicate that even in a sample of *employed* workers, there are still gender differences that play a role in the workers' reaction to changes in commuting costs. See similarly White (1986); Hersch and Stratton (1994).

4. Conclusion

This paper analyses the effect of costs of commuting, measured by the commuting distance, on labour supply patterns using the socio-economic panel data for Germany between 1997 and 2007. As far as we are aware, theoretical and empirical work that focuses on how daily hours respond to changes in commuting distance is analysed here for the first time. We deal with the endogeneity of commuting distance by means of a worker first-differences approach for a sample of employer-induced changes in commuting distance (which are result of workplace relocation, so we keep job and residence location constant). Although one may have intuitive feelings about the effects of commuting distance on total labour supply, the theoretical model developed in this paper demonstrates that empirical analysis is needed, as it is not clear what the direction of the effect is. Nevertheless, we are able to show that theoretically and empirically distance unambiguously increases daily labour supply.

The estimated positive effect of distance on daily labour supply is consistent with the theoretical labour model developed. It is however also consistent with other explanations. One other explanation may be that workers may reduce commuting costs by leaving earlier from home or departing later from work in line with bottleneck economic models (Vickrey, 1969; Arnott et al., 1993). When individuals leave earlier from home or depart later from work (e.g. workers with fixed work schedules), they will increase labour supply, whereas the number of workdays remains constant.

In the current paper, we have emphasized the importance of the assumptions regarding modelled labour supply patters. In particular, how workers may choose their daily labour supply as well as number of workdays are fundamental assumptions. Our empirical results show a slight positive effect of commuting distance on weekly labour supply. The latter effect is the result of a positive effect on daily working hours and a negligible effect on number of workdays. Hence, one implication of our results is that when workers face changes in their commuting costs, they are more likely to change the number of hours worked per day than the number of workdays.

We find that the effect of commuting distance on overall labour supply is rather small, so one other implication of our results is that when aiming to evaluate policies related to changes in commuting costs (e.g. regulation of housing construction), arguments related to changes in labour supply patterns are likely not fundamental to the discussion to what extent these policies affect welfare. Our empirical results seem therefore in contrast to assumptions in the literature that analyse optimal road taxation given distortionary labour income taxation (see e.g. Parry and Bento, 2001; Calthrop, 2001). Our results suggest that when introducing a road tax, a budget-neutral reduction in the income tax, as advocated in the literature (Parry and Bento, 2001; Mayeres and Proost, 2001), may not be necessary in order to increase welfare. Note however that our results need to be interpreted with some caution, because we focus on employed workers only and do not consider the effect of changes in commuting costs/time on labour market participation.[29]

As emphasised in the introduction, our empirical analysis may help us to understand long-term developments in labour supply patterns. Our results suggest that increases in commuting costs may have some effects on daily labour supply. This may help us to understand why in countries such as the Netherlands workers have shifted from the eight hour workdays to nine hour workdays. To what extend our results can explain different trends in labour supply over the last two decades (e.g. in UK and US, labour supply has been rising, whereas in other countries it has been falling), remains open to debate.

[29] There are also other reasons why road pricing may have little effect on the participation decision. Female workers with few working hours for whom the participation decision is strongest affected by economic incentives, do not belong to the same group of workers who generally will face a road tax. Female workers with few hours of work are less likely to travel by car and have shorter commuting distances if they travel by car, so this group will be hardly affected by road pricing.

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Table 1. *Mean Employer-Induced Change in Commuting Distance (1997, 1999–2000, 2002, 2004–2007 GSOEP)*

Change in commuting distance	*Δ* km ≤ –5	|*Δ* km| < 5	*Δ* km ≥ 5
Δ Daily hours	–0.003 (0.166)	0.002 (0.140)	0.015 (0.166)
Δ Workdays	0.006 (0.146)	–0.001 (0.111)	–0.002 (0.110)
Δ Weekly hours	–0.003 (0.218)	0.002 (0.172)	0.014 (0.210)
No. observations	1,341	16,563	1,499

Note: Daily hours, workdays per week and weekly labour supply in logarithm.
Standard deviations in parentheses.

Table 2. *Correlations of Dimensions of Labour Supply (1997, 1999–2000, 2002, 2004–2007 GSOEP)*

	Daily hours	Workdays per week
All workers (N= 19,403)		
Workdays per week	0.218	
Weekly hours	0.381	0.185
Male workers (N= 10,548)		
Workdays per week	0.154	
Weekly hours	0.258	0.083
Female workers (N= 8,855)		
Workdays per week	0.156	
Weekly hours	0.422	0.217

Notes: Pearson correlations; all correlations are significant at 0.05 level (2-tailed).

Table 3. *Estimates of Logarithm of Changes in Labour Supply with Changes in Commuting Distance (1997–2007 GSOEP)*

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	2SLS
	Observed weekly hours			Preferred weekly hours			Workdays per week			Daily hours			
Commuting distance	0.008	0.009	0.009	0.003	0.003	0.003	0.001	0.001	0.001	0.010	0.010	0.010	0.006
	(0.002)**	(0.002)**	(0.002)**	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)**	(0.003)**	(0.002)**	(0.004)
Weekly hours													0.374
													(0.245)
Hourly wage		0.039			–0.090			0.009			0.029		0.029
		(0.034)			(0.068)			(0.033)			(0.036)		(0.036)
New state		–0.009	–0.009		–0.000	–0.001		–0.007	–0.007		–0.013	–0.013	–0.005
		(0.003)**	(0.003)**		(0.004)	(0.005)		(0.004)	(0.004)		(0.006)**	(0.005)**	(0.008)
Other household income/10		–0.035	–0.039		–0.012	–0.004		–0.026	–0.027				
		(0.012)**	(0.011)**		(0.014)	(0.015)		(0.008)**	(0.010)**				
Female × children		–0.053	–0.053		–0.044	–0.044		–0.022	–0.022		–0.027	–0.027	–0.009
		(0.005)**	(0.005)**		(0.010)**	(0.007)**		(0.009)**	(0.004)**		(0.009)**	(0.005)**	(0.015)
Child		–0.019	–0.018		–0.003	–0.006		–0.013	–0.013		–0.013	–0.012	–0.004
		(0.005)**	(0.005)**		(0.008)	(0.007)		(0.006)**	(0.004)**		(0.006)**	(0.005)**	(0.009)
Household members		–0.004	–0.004		–0.008	–0.008		–0.002	–0.002		–0.001	–0.001	0.000
		(0.002)**	(0.002)**		(0.003)**	(0.003)**		(0.002)	(0.002)		(0.002)	(0.002)	(0.003)
F (instr. *wage*)		168.92			73.13			97.65			98.00		97.65
F (instr. *weekly hours*)													12.822
No. observations	41,611	41,611	41,611	29,376	29,376	29,376	19,403	19,403	19,403	19,403	19,403	19,403	19,403

Notes: Year controls included. Weekly labour supply, preferred weekly labour supply, workdays per week, daily hours, commuting distance, net hourly wage rate and monthly net income of other household members in logarithm. Note that for some workers information on preferred weekly labour supply is missing. F-test = Kleibergen-Paap weak identification test. **, * – indicate that estimates are significantly different from zero at 0.05 and 0.10 level. Standard errors are in parentheses. Net hourly wage in columns [2], [5], [8], [11] and [13] is instrumented using the first step of Table B2; weekly labour supply in column [13] is instrumented using the first step of Table B3.

Table 4. *Estimates of Logarithm of Changes in Labour Supply with Changes in Commuting Distance for Male and Female Workers (1997–2007 GSOEP): OLS Approach*

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Observed weekly hours	Preferred weekly hours	Workdays per week	Daily hours	Observed weekly hours	Preferred weekly hours	Workdays per week	Daily hours
	Male workers				Female workers			
Commuting distance	0.0035 (0.0017)**	–0.002 (0.003)	0.001 (0.001)	0.005 (0.002)**	0.015 (0.003)**	0.008 (0.005)*	0.001 (0.003)	0.016 (0.004)**
New state	–0.005 (0.004)	0.004 (0.005)	–0.002 (0.004)	–0.007 (0.005)	–0.012 (0.006)**	–0.004 (0.008)	–0.012 (0.008)	–0.018 (0.010)*
Other household income/10	–0.008 (0.010)	0.003 (0.014)	–0.007 (0.008)		–0.096 (0.024)**	–0.012 (0.032)	–0.062 (0.024)**	
Number of children					–0.026 (0.008)**	–0.023 (0.011)**	–0.004 (0.007)	–0.010 (0.009)
Child	–0.005 (0.004)	0.006 (0.007)	–0.003 (0.003)	–0.002 (0.004)	–0.064 (0.011)**	–0.041 (0.016)**	–0.043 (0.010)**	–0.041 (0.012)**
Household members	–0.000 (0.002)	–0.005 (0.003)	–0.001 (0.001)	–0.000 (0.002)	–0.015 (0.004)**	–0.015 (0.006)**	–0.006 (0.003)*	–0.006 (0.004)
No. observations	22,445	16,033	10,548	10,548	19,166	13,343	8,855	8,855

Notes: Year controls included. Weekly labour supply, preferred weekly labour supply, workdays per week, daily hours, commuting distance and monthly net income of other household members in logarithm. **, * – indicate that estimates are significantly different from zero at 0.05 and 0.10 level. Standard errors are in parentheses.

Appendix A: Theoretical Model

A.1. First-Order Conditions

Using standard microeconomic techniques (see e.g. Varian, 1992), we derive the workers' optimally chosen daily work time H and days D by maximising v, implying the following two first-order conditions:

$$V_Y w'(H)D - V_L D = 0, \tag{A1}$$

and

$$V_Y \left[w(H) - kc\right] - V_L \left[H + t\right] = 0. \tag{A2}$$

The first condition (A1) states that the worker's marginal utility of leisure time equals the marginal opportunity cost of leisure time. The second condition (A2) states that the worker's marginal utility of working *one* day equals the marginal opportunity costs of working *one* day. Equation (1) in the main text is obtained by combining (A1) and (A2).

A.2. Comparative Statics

We label F_1 and F_2 as the two first-order conditions (A1) and (A2) of the worker's optimization problem for H and D. The Hessian matrix M of the first-order conditions can written as:

$$M = \begin{bmatrix} \frac{\partial F_1}{\partial H} & \frac{\partial F_1}{\partial D} \\ \frac{\partial F_2}{\partial H} & \frac{\partial F_2}{\partial D} \end{bmatrix},$$

where:

$$\frac{\partial F_1}{\partial H} = V_Y w''(H)D + V_{YY} \left[w'(H)D\right]^2 - V_{YL} w'(H)D^2 - V_{LY} w'(H)D^2 + V_{LL} D^2 < 0,$$

$$\frac{\partial F_1}{\partial D} = V_Y w'(H) - V_L + Dw'(H)\left[V_{YY}\left[w(H) - kc\right] - V_{LY}\left[H + t\right]\right] - V_{LY}\left[w(H) - kc\right]D + V_{LL} D\left[H + t\right] < 0,$$

$$\frac{\partial F_2}{\partial H} = V_Y w'(H) - V_L + \left[w(H) - kc\right]D\left[V_{YY} w'(H) - V_{YL}\right] - V_{LY} w'(H)D\left[H + t\right] + V_{LL} D\left[H + t\right] < 0,$$

$$\frac{\partial F_2}{\partial D} = V_{YY}\left[w(H)-kc\right]^2 - V_{YL}\left[w(H)-kc\right]\left[H+t\right] - V_{LY}\left[w(H)-kc\right]\left[H+t\right] + V_{LL}\left[H+t\right]^2 < 0.$$

The sign of the derivatives follows from the assumptions regarding *v* and *w*(*H*). The determinant of *M* is positive, which implies a global maximum. We proceed now by using the restriction that $t = k/s$, where *s* is exogenous ($s > 0$).

Partial effects are usually determined based on Cramer's rule. However, the effect of commuting distance *k* on workhours *H* is more easily determined by totally differentiating (1) with *k* and putting this expression equal to zero. Then, $\partial H/\partial k$ can be expressed by:

$$\partial H/\partial k = \frac{-\left[sc + w'(H)\right]^2}{Hw''(H)sc\left[sc + w(H)H\right]} > 0, \qquad \text{(A3)}$$

where the inequality in this expression follows from the concavity of *w*(*H*). The denominator and the numerator in this expression is negative, so $\partial D/\partial k$ is unambiguously determined and is positive.

We apply Cramer's rule to obtain the partial effects of *k* on *D*:

$$\frac{\partial D}{\partial k} = \begin{vmatrix} \frac{\partial F_1}{\partial H} & -\frac{\partial F_1}{\partial k} \\ \frac{\partial F_2}{\partial H} & -\frac{\partial F_2}{\partial k} \end{vmatrix} M^{-1}, \qquad \text{(A4)}$$

where:

$$\frac{\partial F_1}{\partial k} = -V_{YY}w'(H)D^2c - V_{YL}w'(H)\frac{D^2}{s} + V_{LY}D^2c + V_{LL}\frac{D^2}{s},$$

$$\frac{\partial F_2}{\partial k} = -V_Yc - \left[w(H)-kc\right]D\left[V_{YY}c + \frac{V_{YL}}{s}\right] - \frac{V_L}{s} + V_{LY}\left[H + \frac{k}{s}\right]Dc + V_{LL}\left[H + \frac{k}{s}\right]\frac{D}{s},$$

the signs of two out of four derivatives are ambiguous (because time and commuting costs have opposite effects on F_1 and F_2).

The expression for $\partial D/\partial k$ is complicated and not insightful, and can be received upon request. However, it can be easily shown that the sign of $\partial D/\partial k$ is indeterminate. For example, if only time costs of commuting exist (c = 0), the effect of k is equal to the partial effect of t, which has a negative effect on D (see Gutiérrez-i-Puigarnau and van Ommeren, 2009). However, if only monetary costs exists (t = 0), the workers' utility function is $v = \log(Y) + f(L)$, so $V_{YL} = V_{LY} = 0$, $V_Y = 1/Y$, $V_{YY} = -V_Y/Y$, and kc is small relative to $w(H)$, it can be easily shown that $\partial F_2/\partial k = 0$. Hence, an increase in monetary costs has a positive effect on D (meaning that workhours increase to compensate for the loss in income) so $\partial(DH)/\partial k > 0$.

Appendix B: Tables

Table B1. *Distribution of Daily Hours and Workdays per Week (Percent) (1997, 1999–2000, 2002, 2004–2007 GSOEP)*

	Workdays per week			
Daily hours	1–4	5	6–7	All days
	Workers (N= 19,403)			
Less than or equal to 4 h	1.5	4.0	0.5	6.1
More than 4 or less than 7 h	2.3	8.0	1.0	11.3
Exactly 7 or less than 8 h	0.9	14.0	1.0	15.9
Exactly 8 h	1.1	31.5	2.2	34.6
More than 8 or less than 10 h	0.7	18.3	1.3	20.4
Exactly or more than 10 h	0.4	9.0	2.3	11.7
All hours	7.1	84.8	8.1	
	Male workers (N= 10,548)			
Less than or equal to 4 h	0.1	0.2	0.0	0.3
More than 4 or less than 7 h	0.2	1.0	0.3	1.5
Exactly 7 or less than 8 h	0.4	15.2	0.9	16.6
Exactly 8 h	0.4	37.3	2.6	40.3
More than 8 or less than 10 h	0.3	22.5	1.7	24.6
Exactly or more than 10 h	0.3	13.0	3.4	16.7
All hours	1.8	89.2	9.0	
	Female workers (N= 8,855)			
Less than or equal to 4 h	3.2	8.6	1.0	12.9
More than 4 or less than 7 h	4.8	16.3	1.8	22.9
Exactly 7 or less than 8 h	1.6	12.5	1.1	15.2
Exactly 8 h	2.0	24.6	1.4	27.9
More than 8 or less than 10 h	1.2	13.3	0.8	15.3
Exactly or more than 10 h	0.6	4.3	0.9	5.8
All hours	13.4	79.6	7.0	

Notes: Totals do not add to 100% because of rounding.

Table B2. *First Step Results of the Logarithm of Changes in the Net Hourly Wage Rate IV Procedure (1997–2007 GSOEP)*

Variables	Workers	Male workers	Female workers
Instruments			
Age/10	–0.020 (0.001)**	–0.020 (0.001)**	–0.019 (0.002)**
Age^2/100	0.017 (0.001)**	0.016 (0.001)**	0.017 (0.002)**
Control factors			
Change in commuting distance	–0.002 (0.002)	–0.000 (0.003)	–0.005 (0.003)
Change in new state	0.004 (0.004)	0.002 (0.005)	0.005 (0.006)
Change in other household income/10	–0.095 (0.013)**	–0.066 (0.015)**	–0.152 (0.026)**
Change in female × children	–0.007 (0.006)		0.003 (0.008)
Change in child	0.018 (0.006)**	0.023 (0.006)**	0.003 (0.012)
Change in household members	–0.003 (0.002)	–0.002 (0.003)	–0.005 (0.004)
No. observations	41,611	22,445	19,166

Notes: Year controls included. Commuting distance, weekly labour supply, net hourly wage rate and monthly net income of other household members in logarithm. **, * – indicate that estimates are significantly different from zero at 0.05 and 0.10 level. Standard errors are in parentheses.

Table B3. *First Step Results of the Logarithm of Changes in Weekly Labour Supply IV Procedure (1997, 1999–2000, 2002, 2004–2007 GSOEP)*

Variables	Workers
Instrument	
Other household income/10	–0.047 (0.016)**
Control factors	
Change in commuting distance	0.012 (0.003)**
Change in new state	–0.021 (0.007)**
Change in female × children	–0.049 (0.006)**
Change in child	–0.025 (0.006)**
Change in household members	–0.003 (0.003)
No. observations	19,403

Notes: Year controls included. Commuting distance, weekly labour supply, net hourly wage rate and monthly net income of other household members in logarithm. **, * – indicate that estimates are significantly different from zero at 0.05 and 0.10 level. Standard errors are in parentheses.