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DISCUSSION PAPER SERIES

IZA DP No. 10875

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ABSTRACT

Working from Home and the Willingness to Accept a Longer Commute

It is generally found that workers are more inclined to accept a job that is located farther away from home if they have the ability to work from home one day a week or more (telecommuting). Such findings inform us about the effectiveness of telecommuting policies that try to alleviate congestion and transport related emissions, but they also stress that the geography of labour markets is changing due to information technology. We argue that estimates of the effect of working from home on commuting time are biased downward because most studies ignore preference based sorting (self-selection): workers who dislike commuting, and hence have shorter commutes, might also be more likely to work from home. In this paper we investigate to what extent working from home affects the willingness to accept a longer commute and we control for preference based sorting. We use 7 waves of data from the Dutch Labour Supply Panel and show that on average telecommuters have a 50 percent higher marginal cost of one-way commuting time, compared to non-telecommuters. We estimate the effect of telecommuting on commuting time using a fixed-effects approach and we show that preference based sorting biases cross-sectional results 27-28 percent downwards. Working from home allows people to accept 5.7 percent longer commuting times on average, and every additional 8 hours of working from home are associated with 3 percent longer commuting times.

JEL Classification: J32, R11, R41

Keywords: telecommuting, commuting time, job search, job mobility, labour market area

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1 Introduction

There is an ongoing debate about the extent to which working from home (also called telecommuting) affects length of the commute people are willing to accept. Early interest in the effect of telecommuting on commuting distance and household travel was mainly aimed at establishing whether telecommuting could be an effective policy instrument to alleviate congestion and emissions associated with car use (Salomon 1985; Nilles 1991; Lund and Mokhtarian 1994). Increasingly, attention is being given to the notion that telecommuting also affects the geography of labour markets, for example, by having a positive effect on job accessibility (Muhammad et al. 2008; Van Wee et al. 2013). Understanding the relationship between telecommuting and the length of the commute may thus both inform policies aimed at alleviating congestion and transport related emissions, and policies that aim to improve the economic performance of cities and regions.

Most empirical work on the effects of working from home on commuting tends to corroborate the intuitive notion that being able to avoid the commute one day in the week makes workers more willing to accept a longer commute on the other days of the week (Jiang 2008; Zhu 2012; Kim et al. 2015). However, estimates for the size of this effect vary across the literature, the set of control variables included differs between studies, and there is little attention for the intensity of telecommuting (the number of days per week/month). Moreover, there is no consensus on a strategy to deal with sources of bias stemming from the fact that commute length and telecommuting are often decided upon simultaneously. While some studies aim to eliminate the positive reverse causality bias that arises if long commutes influence the decision to telecommute (Jiang 2008; Zhu 2012)., there is a lack of attention for preference-based sorting, potentially leading estimates of the effect of working from home on commuting to be biased downwards. Workers who dislike commuting, and hence have shorter commutes, might also be more likely to work from home. So the real effect of working from home on commuting behaviour, and thereby on the geography of labour markets, might be larger than assumed up to now.

The objective of this study is to find out to what extent controlling for preference-based sorting affects the relationship between telecommuting and the length of the commute. Where earlier research on this subject is largely based on either panel data from specific experiments, or cross sectional data from large scale surveys, we use Dutch data from a panel survey, representative of the Dutch working age population, spanning 12 years. In the first part of our analysis we provide evidence that preferences for commuting differ between telecommuters and non-telecommuters by comparing the marginal costs of one-way commuting time (MCC) of both groups. To estimate the MCC we use job search and job mobility models, following the approach of Van Ommeren and Fosgerau (2009). The panel structure of the data then allows us to model commuting time and examine to what extent such individual preferences bias cross sectional results, through preference-based sorting. We do this by comparing OLS estimates of commuting time to the results of a fixed effects model that controls for unobservable time invariant characteristics of respondents. Finally in the sensitivity analysis we apply an even stricter identification method based on the timing and intensity of telecommuting, and we allow for a non-linear effect of weekly hours spent working from home.

2 Telecommuting and the length of the commute

2.1 Theoretical implications of telecommuting

The potential spatial effects of telecommuting, and other ICT activities have been theorized upon for at least 50 years. According to Webber (1963), the observed spatial expansion of market areas during the 1960s due to, inter alia, information flows was indicative of a looming ``demise of the city'' (Webber 1963, p. 1099). Such visions were generally based on the idea that information and communications technology would eventually substitute face-to-face contact, and have been a recurrent theme in futurist writings on the death of cities, and the death of distance (Toffler 1980; Naisbitt 1994; Cairncross 1997).

In much of the literature, telecommuting is seen as a potential policy instrument to decrease car-travel, of which the effectiveness is dependent on the overall effect on travel. In transportation research it is often stressed that telecommuting, and ICT activities in general, may substitute, complement, modify, or neutrally affect travel (Salomon 1985). The notion of complementary travel is based on the idea that telecommuting may induce people to accept jobs over longer distances, making the net travel effects of telecommuting not necessarily negative. Furthermore, it is argued that households have a rather fixed mobility budget, and a decrease in trips for commuting would be substituted by leisure trips, and trips of other household members (De Graaff 2004).

However, the welfare effects of telecommuting may stretch further, because workers that are able to telecommute can expand the geographical areas in which they look for jobs (Van Wee et al. 2013). Basic urban economic models support the intuition that if telecommuters have less commuting trips than non-telecommuters, they bid less for homes closer to the

Central Business District (the location of employment), and more for suburban homes (Alonso 1974; Lund and Mokhtarian 1994; Jiang 2008). Rhee (2008) shows that in theory, similar results could be obtained in cities with dispersed employment. In situations with little building restrictions, telecommuting may thus in theory promote residential sprawl in a similar way as the automobile did (Glaeser and Kahn 2004). In settings with strict urban containment policies, and a low elasticity of housing supply, such as the Netherlands (Vermeulen and Rouwendal 2007), possibilities for telecommuting may increasingly enable workers to live in one city and reap the benefits of access to labour in other cities (Muhammad et al. 2008; Van Wee et al. 2013).

In the current work we are predominantly interested in the effect of telecommuting on the geographical scale of labour market areas. Therefore we focus on the relatively uncontested mechanism by which telecommuting potentially increases the length of one-way commutes, because it allows workers to commute less frequently. We do not take into account the effects of telecommuting on non-commute trips, and travel behaviour of other household members.

2.2 Empirical issues

Empirical research on the effects of telecommuting on the length of the commute started in the early 1990s, when personal computers started to become a household commodity. In a seminal publication, Nilles (1991) investigates the potential effects of telecommuting on urban sprawl and household travel, using data from a telecommuting experiment with California State workers that spanned two years. He concludes that at the time, telecommuting did not (yet) exacerbate urban sprawl, and that it resulted in decreased household travel. He did however find that telecommuting was associated with moves farther away from the work location, so his findings did not rule out future *telesprawl* as a consequence.

Later evidence on the relationship between telecommuting and the length of the commute is somewhat scattered, in part because of different definitions of telecommuting.[1] In a review of evidence by De Graaff (2004) it is concluded that most studies show a negative relationship between telecommuting and the number of commuting trips, and studies that do investigate the length of the commute find mixed evidence, but do not rule out a positive relationship. Andreev et al. (2010) conclude similarly, and stress that the majority of the literature suffers from problems such as the lack of a universal definition of telecommuting, the external validity of the results, and absence of theoretical substantiation of the results.

[1] Mokhtarian et al. (2005) illustrate that definitions, measurement instruments, sampling, and vested interests affect the quality and utility of data, using telecommuting as a case study.

Recent endeavours increasingly pay attention to potential sources of bias that influence the results from observational studies. These sources can be divided into (1) omitted variables, (2) reverse causality, and (3) preference-based sorting. With respect to omitted variables, the advent of large scale surveys in which questions about telecommuting were asked, made it possible to control for a variety of respondent characteristics, and also made it possible to assess telecommuting across different industries. A notable work in this respect is (Kim et al. 2012), who estimated the effect of telecommuting on peripheral living, controlling extensively for household characteristics including income, and job locations. Accounting for wage seems particularly relevant in telecommuting research, because earnings and telecommuting status tend to be correlated (Muhammad et al. 2008).

Jiang (2008, p. 10) provides a clear-cut definition of the other two types of bias involved in the relationship between telecommuting and commuting distance, and the direction of these biases: "If [a] longer commute encourages an individual to work from home when allowed, a regression of commute length on telecommuting status will overestimate the effect of telecommuting. On the contrary, telecommuters could be those who feel more pressures from traffic. They would have shorter commutes in the absence of telecommuting opportunities. This unobserved selection will lead to a downward [bias] in the regression estimates." We refer to the first bias he addresses as reverse causality, and to the second as preference-based sorting.

A study in which an attempt is made to overcome the bias from potential reverse causality is done by Zhu (2012). He employs an instrumental variables approach, using the number of phones in a household, and the usage of the internet at home as instruments, argued to influence commuting distance only through the effects on telecommuting. Although the reverse causality bias he refers to should lead to overestimation of the effect of telecommuting, he finds that his IV approach leads to *higher* estimates, compared to OLS. According to his IV results for the year 2009, telecommuters that work from home at least once a week have a 1576 percent longer commuting distance, and a 160 percent longer commuting duration on average.[2] While these estimates are large, the results suggest that the bias not accounted for in OLS models is positive rather than negative.

Jiang (2008) uses a similar IV approach, but the instruments in this study are based on the penetration of home-based teleworking across combinations of occupations and city size

[2] Given his log-linear model, these are the marginal effects of the telecommuting dummy for which the point estimate is 2.819 for the distance model, and 0.993 for the duration model. The marginal effects are calculated as $(e^{\beta} - 1) * 100\%$. The corresponding marginal effects of his OLS estimates are more realistic: 23 and 19 percent respectively.

classes. The results of this study show that OLS tends to underestimate the real effect of telecommuting. While the OLS estimates in this study show that, at least for married women, telecommuting increases commuting time by 3 minutes, the IV estimates suggest an effect of 9 to 11 minutes. No significant results are found for men, and single women.

The current study addresses several gaps that emerge from the literature. First, next to household characteristics we include detailed job characteristics as control variables, including monthly wage, the type of industry, the type of employment, and the usual number of work days per week. Especially the latter control is a novelty in this type of research. Second, we make use of the time dimension of our data, and we focus on the effect of *changes* in telecommuting status, on *changes* in commuting time. Arguably, this makes the potential bias of reverse causality less pressing. While exogenous changes in commuting time (for instance due to firm relocations) may influence the decision to telecommute, this still indicates that telecommuting increases the willingness to accept a longer commute. Finally, the time dimension of the data also allows us to control for all time-invariant characteristics of respondents through the use of fixed effects models. Such time invariant characteristics include unobserved preferences for commuting, so this approach allows us to address the negative bias due to preference-based sorting. This is one of the first studies to address the relationship between telecommuting and commuting distance with a fixed effects approach.[3]

3 Data and methods

3.1 Data description

Our empirical analyses are based on data from the Netherlands. The urban landscape of the Netherlands is characterized by a polycentric urban structure with many small- and medium sized cities. Labour- and housing markets stretch far beyond cities, and it is relatively common to live in or near one city, and work in another urban area (Burger and Meijers 2016). Another notable characteristic if the concentration of employment in the Randstad area, in the west of the country. This area is also characterized by a higher wage level (Groot et al. 2014), and better matching between workers and employers indicated by lower levels of overeducation (Büchel and Van Ham 2003). In the Netherlands telecommuting is a relatively widespread phenomenon, due to the mass adoption of ICT, the high share of the tertiary sector

[3] Two notable studies that apply a fixed effects to approach to telecommuting research are De Graaff (2004), who looks at the relationship between telecommuting and total travel, and Kolko (2012), who aims to uncover how broadband availability affects the adoption of telecommuting.

in economic activities, and the high population density and the associated congestion problems (Muhammad et al. 2007, 2008).

The data we use comes from the Labour Supply Panel (SCP 2016), and it consists of the 7 latest biannual waves (between 2002 and 2014). While the panel has been running since 1985, 2002 is the first year in which questions were asked about the degree to which people work from home. We have 21,070 observations for 8,625 individuals, and for 326 individuals we have data for all years.[4]

We are interested in the relationship between working from home and the (accepted) commuting time. Two questions from the survey we use relate to the intensity of teleworking. The first asks to state how many days per month respondents work from home usually. The answers to this question are measured on an ordinal scale with 5 possibilities (0, 1, 2, and 3 days, and more than 3 days). The second question asks to state the average number of weekly hours spent from home in the 4 weeks before the survey date, and the resulting variable is measured on a continuous scale. We will perform our analyses using (1) a dummy that indicates whether or not a respondent telecommutes 1 day or more per month, (2) an ordinal factor variable that denotes the usual number of telecommuting days per month, and (3) a continuous measure of the average number of hours working from home. Figure 1 shows the time patterns of the share of respondents that work at least 1 day from home per month, and the average weekly hours working from home. While the share of people that work from home at least once a month is volatile across the years, ranging between 0.31 and 0.35, the usual number of weekly hours spent working from home shows a sharp increase beyond 2010. The latter fact stresses that in terms of intensity, working from home is still a dynamic and upcoming trend.

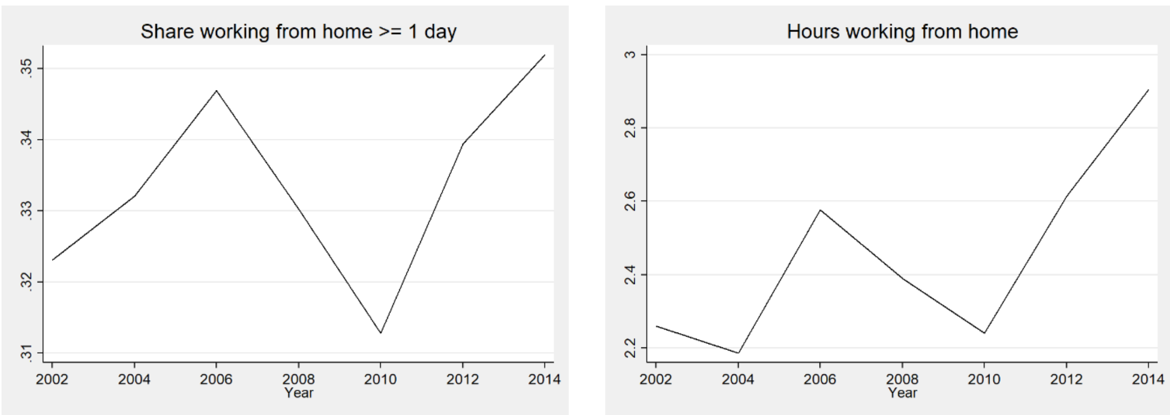

Figure 1: Time patterns of working from home

[4] We excluded extreme observations with commuting times longer than 500 minutes and daily wages higher than €1,000.

Commuting time is measured as the usual time it takes to get to work from the residential location. The data does not contain information on commuting distance. However, modelling commuting distance is generally plagued by assumptions about mode choice and commuting speed (Isacsson et al. 2013), while the use of commuting time can be justified by the assumption that commuting speed is optimally chosen (Van Ommeren and Fosgerau 2009). Figure 2 shows the (kernel) distribution of one way commuting time for non-telecommuters, occasional telecommuters (up to 3 days per month), and regular telecommuters (more than 3 days per month). The figure shows that the distribution of commuting times for non-telecommuters has its bulk between 0 and 25 minutes, while the distributions of the other categories are more spread, including relatively longer commutes. The average commuting time for non-telecommuters is 22 minutes, versus 31 minutes for occasional telecommuters, and 30 minutes for regular telecommuters. So far, it seems that non-telecommuters have considerably shorter commutes on average, while regular telecommuters do not have longer commuting times than occasional telecommuters.

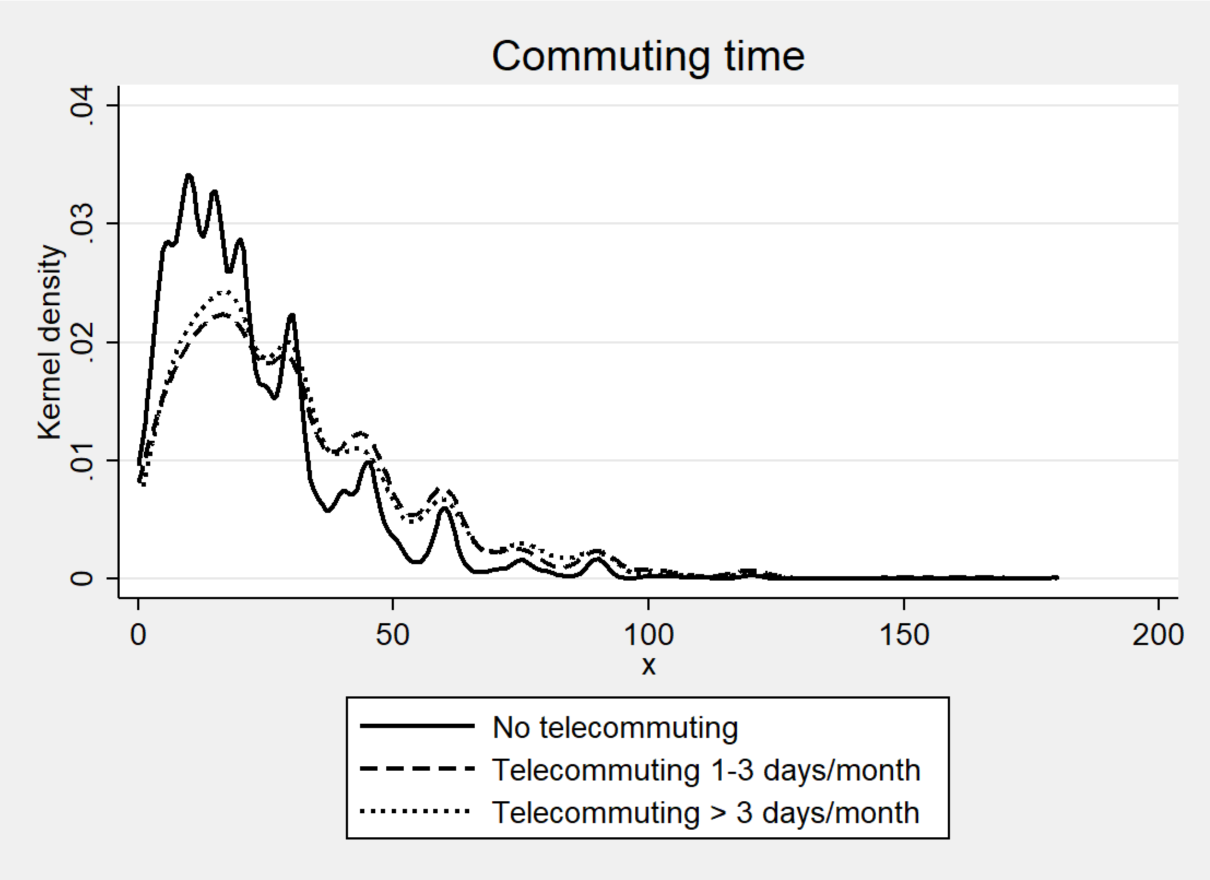

Figure 2: Distribution of commuting time according to telecommuting status. The density functions are estimated with a Gaussian kernel, and a rule-of-thumb bandwidth.

Other essential variables are all deduced from answers to questions in the survey: We calculate the daily wage of respondents based on the (stated) net wage per month and the usual number of working days per week, assuming 6 weeks of vacation on average; job search is measured as a dummy indicating the respondent is searching for a job at the moment the survey was conducted; job mobility is measured as a dummy that indicates whether or not the respondent changed jobs between two consecutive survey waves, and in our analysis we use the 2-year lead of this variable.

Table 1 shows the summary statistics of the full sample used in the first part of our analysis, including the average number of working days per week, firm sector and size, age, sex, the presence of children and a partner, and the wage of the partner. The summary statistics of the restricted sample of individuals for which we have information for all years are presented in Table 5, Appendix A: Supplementary tables. Individuals in this part of the panel are less likely to search for, or change jobs, they have somewhat longer commutes on average, and they are slightly more prone to telecommute.

3.2 Methods

Preference-based sorting may be an issue when people who dislike commuting, and would have short commuting times in the first place, choose to telecommute. As elaborated upon in section 2, such behaviour biases regression results downward. In the first part of our empirical analysis we use a model based on job search theory to calculate the marginal monetary value of one-way commuting time (MCC) both for telecommuters and non-telecommuters separately. If the MCC is significantly higher for telecommuters, we interpret this as evidence for preference-based sorting.

Using the job search approach we relate commuting time and wage levels with each other through their effects on (1) on-the-job search, and (2) job mobility (Van Ommeren and Fosgerau 2009). The intuition behind this approach is that workers are not in their preferred job per se, and are able to improve upon their situation by searching for jobs, and moving jobs if they find a better fit that improves their *lifetime* utility (Van Ommeren et al. 2000). By calculating the effect of commuting time on job search and job moving, we get an indication of the willingness to accept longer commuting times. Moreover, by calculating the ratio of the effect of commuting time and the effect of wages, we can put a monetary value on this willingness to accept (Van Ommeren and Fosgerau 2009). The advantage of this approach is that we do not need to assume that labour markets are in equilibrium (Gronberg and Reed

1994). In other words, we do not need to assume that observed situations in the labour market reflect the best choices among all available alternatives.

Table 1: Summary statistics full sample

Variables	N	Mean	Std. dev.	Min.	Max.
No telecommuting	21,070	0.666	0.472	0	1
Telecommuting >= 1 day/month	21,070	0.334	0.472	0	1
Telecommuting 1 day/month	21,070	0.101	0.301	0	1
Telecommuting 2 days/month	21,070	0.0761	0.265	0	1
Telecommuting 3 days/month	21,070	0.0772	0.267	0	1
Telecommuting >3 days/month	21,070	0.0801	0.271	0	1
Telecommuting weekly hours	21,070	2.462	6.882	0	97
Commuting time	21,070	25.20	20.89	0	180
Job search at t	21,070	0.109	0.312	0	1
Job move between t-2 and t	21,070	0.162	0.368	0	1
Job move between t and t+2	12,430	0.112	0.316	0	1
Daily wage	21,070	98.76	48.19	0.574	808.7
Monthly wage	21,070	1,580	879.8	11	16,667
Working days/week	21,070	4.094	1.193	1	7
Firm size	21,070	571.2	2,475	0	100,000
Age	21,070	41.57	12.27	16	66
Female	21,070	0.492	0.500	0	1
Partner	21,070	0.751	0.432	0	1
Partner wage	21,070	1,095	2,506	0	75,000
Children at home	21,070	0.540	0.498	0	1
Primary education	21,070	0.0280	0.165	0	1
Basic education	21,070	0.201	0.401	0	1
Higher education	21,070	0.391	0.488	0	1
Vocational education	21,070	0.267	0.442	0	1
Bachelor degree	21,070	0.113	0.317	0	1
Sector: Agriculture	21,070	0.00897	0.0943	0	1
Sector: Industry	21,070	0.113	0.317	0	1
Sector: Construction	21,070	0.0374	0.190	0	1
Sector: Trade	21,070	0.161	0.367	0	1
Sector: Transport	21,070	0.0581	0.234	0	1
Sector: Business services	21,070	0.168	0.374	0	1
Sector: Healthcare	21,070	0.203	0.402	0	1
Sector: Other	21,070	0.0471	0.212	0	1
Sector: Government	21,070	0.0956	0.294	0	1
Sector: Education	21,070	0.108	0.311	0	1
Jobtype: Civil servant	21,070	0.173	0.379	0	1
Jobtype: Employee	21,070	0.816	0.387	0	1
Jobtype: Director	21,070	0.00835	0.0910	0	1
Jobtype: Self-employed w/ personell	21,070	0.000854	0.0292	0	1
Jobtype: Self-employed w/o personell	21,070	0.000807	0.0284	0	1

Conceptually, our regression model distinguishes between telecommuting as a job asset, and telecommuting as a substitute for commuting physically. We investigate the effect of telecommuting on the acceptability of one-way commuting times by examining the interactions between a telecommuting dummy and commuting distance. The main effect of this telecommuting dummy tells us something about the intrinsic value of telecommuting. Several studies suggest for instance that working from home on designated, individual tasks may increase worker productivity (Bernardino 2017). Furthermore, the possibility to telecommute may increase the chance of matching between workers and employers if labour markets for telecommuting jobs indeed have a larger geographical scale.

In the second part of the analysis, we estimate the extent of the bias due to preference-based sorting by comparing the outcomes of an OLS commuting time regression, to the results from an individual fixed effects approach that makes use of the panel dimension of the data. The latter method corrects for all time-invariant characteristics of people, including time-constant preferences. We control for time-variant confounders as much as possible by accounting for (changes in) monthly wage, the industry in which people work, the type of employment, whether or not individuals have a partner or kids at home, and the wage of the partner.

4 Results

4.1 Evidence for preference-based sorting

In this subsection we examine the difference in commuting preferences between telecommuters and non-telecommuters. We do this by estimating the effect of commuting time on job search and the propensity to change jobs, for both groups. We standardize this effect by the effects of wage on job search and mobility to obtain the marginal costs of one-way commuting time (MCC), measured as the average amount of daily wage people are willing to give up to shorten their (one-way) commute with 1 minute (Van Ommeren and Fosgerau 2009). First, in Figure 3 we show the bivariate relationship between commuting time and job search and mobility for the whole sample. It is clear that both the share of people looking for a job, and the share of people changing jobs within two years is positively related with commuting time. This confirms the intuitive notion that longer commutes are seen as a negative aspect of jobs.[5]

[5] We found no such clear bivariate patterns between telecommuting and job- search and mobility.

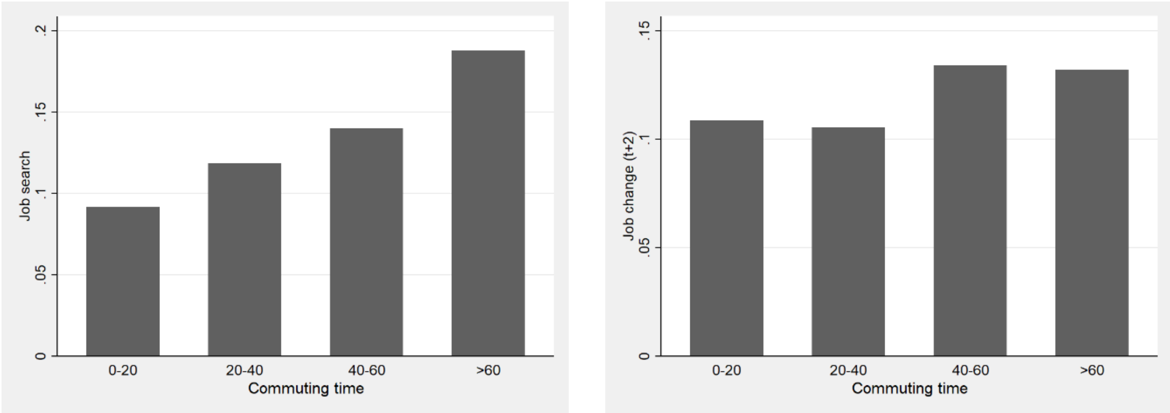

Figure 3: Bivariate relationships between commuting time and job search (l), and job mobility (r)

In Table 2 we estimate the daily MCC using the two distinct approaches. We follow the literature and use a random effects probit model to deal with potential heterogeneity among different individuals.[6] According to the job search model in column (1) commuting time has a greater effect on job search for telecommuters than for non-telecommuters. In monetary terms, non-telecommuters are willing to accept a 1 minute longer one-way commute for €2.89 per work day, while telecommuters are willing to accept a 1 minute longer commute for €4.40.[7] Note that this is in spite of the fact that, by definition, telecommuters commute less frequently, compared to non-telecommuters, so the MCC per commuting trip may be even higher for telecommuters. Furthermore, according to this model age has a positive but marginally decreasing effect on the propensity to search, and higher educated people search more. The effect of telecommuting itself is significant, and according to this model telecommuting more than 1 day per month makes it 11.8 percent less likely to search for a job.[8] This positive effect indicates that telecommuting has value in itself for instance by increasing productivity or by improving the quality of matches on the labour market (due to larger search areas).

In column (2) we estimate the same model with job mobility (changing jobs within two years) as the dependent variable. According to this model the MCC is €2.82 for non-telecommuters, and €4.14 for telecommuters. These values are remarkably similar to the estimates in the previous model, and importantly the ratio between these values is similar too (1.52 vs. 1.47). According to this model the effect of age on mobility is predominantly negative, and higher educated people are more mobile. The effect of telecommuting itself on

[6] This allows the error terms of the same individuals to be correlated over time (Van Ommeren and Fosgerau 2009).
[7] The MCC is derived from the ratio of the effects of commuting time and daily wage.
[8] The probability to search for a job is 11.49 percent for non-telecommuters, and 10.13 percent for telecommuters, all else equal.

job moving is not significant, and the point estimate is smaller, but comparable to the one in the previous model.

In conclusion, this part of the analysis shows that the MCC is about 50 percent higher on average for telecommuters, in spite of the fact that their commuting frequency is lower. Therefore it is established that preferences of telecommuters differ significantly from non-telecommuters in terms of commuting tolerance. More specifically, as it seems that telecommuters value commuting time much higher, not taking into account sorting when analysing the effect of telecommuting on commuting time would lead to underestimation of the real effect.

Table 2: Willingness to pay for commuting regressions

	(1) Job search	(2) Job mobility
Commute * No telecommuting	0.00463***	0.00313**
	(0.000982)	(0.00124)
Commute * Telecommuting >=1 day/month	0.00704***	0.00460***
	(0.00106)	(0.00127)
Telecommuting >= 1 day/month	-0.163***	-0.0993
	(0.0560)	(0.0676)
Daily wage	-0.00116**	-0.00111*
	(0.000499)	(0.000658)
Firm size	3.35e-06	-1.90e-05
	(5.54e-06)	(1.40e-05)
Age	0.119***	0.0103
	(0.0122)	(0.0150)
Age^2	-0.00162***	-0.000448**
	(0.000148)	(0.000185)
Female	0.0711*	0.000464
	(0.0405)	(0.0494)
Partner	-0.174***	-0.142**
	(0.0470)	(0.0582)
Partner wage	-3.78e-06	1.32e-05*
	(6.17e-06)	(6.98e-06)
Children at home	-0.0202	0.0135
	(0.0411)	(0.0504)
Basic education	0.139	0.313**
	(0.123)	(0.128)
Higher education	0.264**	0.339***
	(0.120)	(0.126)
Vocational education	0.538***	0.525***
	(0.126)	(0.133)
Bachelor degree	0.694***	0.555***
	(0.133)	(0.145)
Constant	-4.063***	-0.853***
	(0.269)	(0.307)
Individual random effects	Yes	Yes
Year dummies	Yes	Yes
Control dummies	Yes	Yes
Observations	21,035	12,419
Individuals	8,625	5,024
Rho	0.324	0.224
Log likelihood	-6733	-4029
MCC non-telecommuters	€2.89	€2.82
MCC telecommuters	€4.40	€4.14
Relative difference	1.52	1.47

Notes: Robust std. errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control dummies include 7 working days-, 10 industry-, and 5 job type dummies. MCC stands for Marginal cost of commuting, and should be interpreted as the daily willingness-to-pay for a one minute reduction in one-way commuting time.

4.2 Commuting time

In this subsection we estimate the effect of telecommuting on commuting time, controlling for preference-based sorting by employing individual fixed effects. We start with an OLS model and we compare the resulting estimates with the results of a fixed effects model. For efficient estimation of the fixed effects and to reduce the noise due to individual heterogeneity we only include the 326 individuals for whom we have valid observations for all years.[9] Because the dependent variable is in logs, 16 observations with 0 commuting time are excluded from the analysis, so we are left with 2,266 observations.

Table 3 shows the OLS results. In column (1) we use a telecommuting dummy that equals 1 if an individual usually telecommutes at least 1 day per month. According to this model telecommuting results in a 4.1 percent longer commute on average.[10] Furthermore, a 10 percent increase in daily wage is associated with a 1.6 percent increase in commuting time, the level of education has a positive effect on commuting time, commuting patterns are gendered (women have about 7.2 percent shorter commutes), and individuals with children at home have about 11.3 percent shorter commutes. Except for the insignificant effect of age, these findings are in line with earlier results on Dutch commuting behaviour, which showed that females, and people with children, have shorter commutes on average, and people of higher socio-economic status commute longer (Van Ham 2002; Burger et al. 2014). Employees of larger firms commute longer according to this model.

In column (2) we distinguish between 1, 2, 3, and more than 3 days of telecommuting per month. The results show that the positive effect found in the previous column is mainly driven by telecommuters that telecommute 2 or 3 days per month, as the effects of other telecommuting categories (1 day and >3 days) are small and insignificant. The coefficients of the other variables are virtually unaffected by this alternative measure of telecommuting. In column (3) we measure telecommuting by the usual number of hours per week spent telecommuting. Arguably this is the most precise measure of telecommuting intensity. According to the model every 8 additional hours of telecommuting lead to a 2.2 percent increase in commuting time. The other coefficients are again similar to those in previous models.

[9] A selectivity bias test based on Verbeek and Nijman (1992) suggests that sample attrition is not related to the idiosyncratic errors (i.e. the coefficients of lead and lag terms of selection indicators are not significant in fixed effects models using the full, unbalanced panel).}

[10] The coefficients in these log-linear models should be interpreted as an $(e^{\beta} - 1) * 100\%$ increase for every unit increase. For logged independent variables the coefficients can be interpreted as an elasticity.

Table 3: OLS commuting time regressions. Dependent variable: Commuting time (log)

	(1)	(2)	(3)
Telecommuting >=1 day/month	0.0411**		
	(0.0168)		
Telecommuting 1 day/month		0.00481	
		(0.0242)	
Telecommuting 2 days/month		0.102***	
		(0.0247)	
Telecommuting 3 days/month		0.0650***	
		(0.0244)	
Telecommuting >3 days/month		0.00735	
		(0.0281)	
Telecommuting weekly hours			0.00276**
			(0.00120)
Daily wage (log)	0.161***	0.163***	0.170***
	(0.0279)	(0.0279)	(0.0272)
Firm size	1.12e-05***	1.10e-05***	1.11e-05***
	(2.69e-06)	(2.73e-06)	(2.61e-06)
Age	0.00839	0.00840	0.00899
	(0.00894)	(0.00894)	(0.00895)
Age^2	-0.000106	-0.000106	-0.000113
	(9.73e-05)	(9.73e-05)	(9.74e-05)
Female	-0.0751***	-0.0741***	-0.0745***
	(0.0206)	(0.0206)	(0.0205)
Partner	0.0397*	0.0358	0.0398*
	(0.0238)	(0.0239)	(0.0237)
Partner wage	1.50e-06	1.74e-06	1.45e-06
	(1.67e-06)	(1.68e-06)	(1.69e-06)
Children at home	-0.120***	-0.119***	-0.121***
	(0.0174)	(0.0174)	(0.0174)
Basic education	0.166***	0.163***	0.169***
	(0.0593)	(0.0592)	(0.0595)
Higher education	0.230***	0.227***	0.236***
	(0.0592)	(0.0590)	(0.0593)
Vocational education	0.267***	0.268***	0.274***
	(0.0609)	(0.0607)	(0.0612)
Bachelor degree	0.318***	0.313***	0.326***
	(0.0663)	(0.0661)	(0.0663)
Constant	-0.0996	-0.0854	-0.162
	(0.283)	(0.287)	(0.283)
Year dummies	Yes	Yes	Yes
Control dummies	Yes	Yes	Yes
Observations	2,266	2,266	2,266
R-squared	0.173	0.178	0.173

Notes: Robust std. errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. TC stands for telecommuting and in columns (1) and (2) No Telecommuting is the reference category. Control dummies include7 working days-, 10 industry-, and 5 job type dummies.

In Table 4 we estimate the same models including individual specific fixed effects that correct for all time-invariant attributes of individuals, including preferences. Coefficients are estimated based on variation *within* individuals over time. The results from column (1) indicate that telecommuting leads to 5.7 percent longer commutes, rather than the 4.1 percent estimated in column one. Thus the extent of the bias due to sorting is -28 percent according to this specification. The fixed effects model results in several different coefficients compared to the OLS estimates. First, the effect of daily wage on commuting time is lower when accounting for time-invariant unobservables. This may for instance be driven by correlations between capability and labour mobility. Second, it seems that ageing does not significantly influence commuting time until the age of 46, after which every additional year is associated with a longer commute. This makes sense because younger people may be more willing to move residence. Second, changes in firm size and having children at home do not affect commuting time. Finally, while we see an increasing pattern in the effects of education on commuting, only the effect of obtaining a bachelor degree is significant, and only at the 10 percent confidence level.

Column (2) is the fixed effects equivalent of Table 3, column (2). The results from this column show that compared to non-telecommuters, individuals that telecommute 1 day per month accept a 7.7 percent longer commute, those telecommuting 2 days per month a similar but lower 7.6 percent, those that telecommute 3 days commute 5 percent longer, and those that telecommute more have a 3.3 percent longer commute (only significant at the 10 percent confidence level). This result is somewhat counter-intuitive as it suggests positive but decreasing effect of telecommuting on commuting time. It should however be noticed that the only significant difference in coefficients between *consecutive* categories is the one between no telecommuting and telecommuting 1 day per month. Other coefficients in this model are similar to those in the previous column.

Finally, in column (3) we estimate the effect of (changes in) the usual weekly hours spent working at home on (changes in) commuting time. The effect is estimated at a 3 percent increase in commuting time for every 8 additional weekly hours spent working at home, indicating a 27 percent downward bias due to preference-based sorting in the OLS estimate in column (3), Table 3.

Table 4: FE commuting time regressions. Dependent variable: Commuting time (log)

	(1)	(2)	(3)
Telecommuting >=1 day/month	0.0588***		
	(0.0140)		
Telecommuting 1 day/month		0.0802***	
		(0.0185)	
Telecommuting 2 days/month		0.0789***	
		(0.0198)	
Telecommuting 3 days/month		0.0517***	
		(0.0195)	
Telecommuting >3 days/month		0.0339*	
		(0.0185)	
Telecommuting weekly hours			0.00381***
			(0.000815)
Daily wage (log)	0.107***	0.110***	0.114***
	(0.0289)	(0.0289)	(0.0288)
Firm size	1.83e-06	1.78e-06	1.90e-06
	(2.04e-06)	(2.04e-06)	(2.03e-06)
Age	-0.0152*	-0.0148*	-0.0136
	(0.00883)	(0.00882)	(0.00881)
Age^2	0.000196**	0.000187**	0.000178*
	(9.29e-05)	(9.28e-05)	(9.26e-05)
Partner	0.0416	0.0446	0.0420
	(0.0371)	(0.0371)	(0.0371)
Partner wage	-1.29e-06	-1.41e-06	-1.37e-06
	(1.86e-06)	(1.86e-06)	(1.86e-06)
Children at home	-0.0240	-0.0231	-0.0203
	(0.0186)	(0.0186)	(0.0186)
Basic education	0.0348		
	(0.0576)	(0.0576)	(0.0576)
Higher education	0.0415	0.0421	0.0397
	(0.0608)	(0.0608)	(0.0608)
Vocational education	0.103	0.107*	0.103
	(0.0652)	(0.0652)	(0.0651)
Bachelor degree	0.146*	0.146*	0.147**
	(0.0749)	(0.0748)	(0.0748)
Indiv. fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Control dummies	Yes	Yes	Yes
Observations	2,266	2,266	2,266
R-squared	0.759	0.760	0.760

Notes: Robust std. errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. TC stands for telecommuting and in columns (1) and (2) No Telecommuting is the reference category. Control dummies include 7 working days-, 10 industry-, and 5 job type dummies.

From the analyses in this subsection we conclude that telecommuting significantly affects commuting time and the bias induced by preference-based sorting of individuals into telecommuting is between -27 and -28 percent.[11] According to our results telecommuting allows people to accept 5.7 percent longer commutes on average, and for every 8 additional weekly hours spent working from home, people accept a 3 percent longer commute.

4.3 Sensitivity analysis

In this subsection we subject our results to two sensitivity checks. First, we employ a stricter identification approach based on the timing and intensity of telecommuting. We do this by only analysing individuals that telecommuted *at some point* during the study period. For these individuals we know that they are able to telecommute, so the decision of whether or not to telecommute, and for how many days and hours, suffers less from potentially omitted variables and self-selection. The drawback of this approach is that the external validity of the results is limited, because the effects we obtain in principle only apply to those able to telecommute. The results of these *timing* regressions, presented in columns (1-3) of Table 6, Appendix A: Supplementary tables, are comparable to the estimates from Table 4.

Second, we investigate whether there are nonlinearities in the effect of hours working from home on commuting time. We do this by estimating a dummy specification, in which the variable denoting weekly hours spent working from home is divided up into 7 categories (0, 0-8, 8-16, 16-24, 42-32, 32-40, and 40+). The model, presented in the 4th column of Table 6 in Appendix A: Supplementary tables, is an alternative version of Table 4 column (3), and the marginal effects of the dummies are depicted in Figure 4. While the graph does not show significant effects of telecommuting categories 16-24, 32-40, and 40+ hours per week, the overall pattern of point estimates follows a somewhat linear pattern. Considering the observed pattern, and the significance of the other dummies, we may conclude that the parametric approach in Table 4 column (3) is a reasonable approximation of the non-parametrically estimated shape of the relationship, and as it is more efficient it has our preference. In conclusion, our results are robust to identification based on the timing and intensity of telecommuting, and a linear specification of average weekly hours working from home is not problematic.

[11] The models with a telecommuting dummy suggest a -28 percent bias (5.7 percent (FE) versus 4.1 percent (OLS)), the models with a continuous measure of weekly hours spent working from home suggest a -27 percent bias (3 percent (FE) vs 2.2 percent (OLS)).

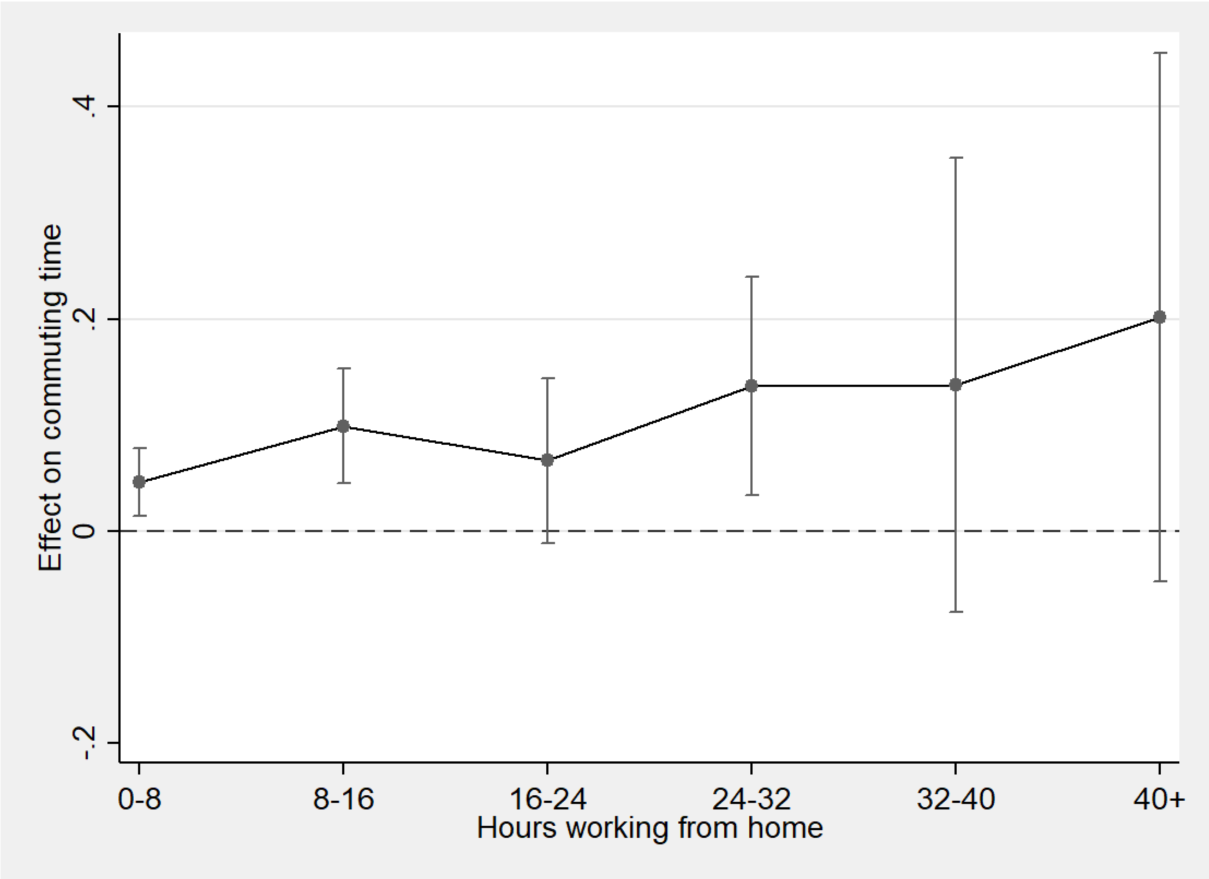

Figure 4: Non-linear effect of hours working from home. No telecommuting is the reference category. The dots represent the point estimates, the vertical lines represent the 95 percent confidence intervals, and the dashed horizontal line represents zero

5 Conclusion

This paper shows that the relationship between telecommuting and commuting time suffers from a bias due to preference-based sorting that should be accounted for: the effects of commuting time on labour search and labour mobility suggest that telecommuters have a much higher (about 50 percent) value of one-way commuting time, despite their lower commuting frequency. In our analysis we show that this sorting bias has a downward effect on OLS estimates in the range of 27 to 28 percent. Our preferred estimates suggest that moving from a situation with no telecommuting, telecommuting allows people to accept 5.7 percent longer commuting times on average, and every additional 8 weekly hours of working from home are associated with 3 percent longer commuting times. These results are robust to a number of sensitivity checks in which we apply an even stricter identification method based on the timing of telecommuting, and allow for a non-linear effect of weekly hours working from home Thus, telecommuting has a significant impact on the commuting distances that people are willing to accept, and with that, on the geographical scale of labour markets.

There are some limitations to the research approach in this paper that could inspire further research. First, we only analyse commuting time, and not commuting distance, because we lack the proper data. Several studies do investigate the effect of telecommuting on both commuting time and distance, and generally find greater elasticities for distance (Andreev et al. 2010; Zhu 2012). Theoretically, focusing on commuting time, and ignoring commuting distance, is justified by assuming that commuting speed is optimally chosen (Van Ommeren and Fosgerau 2009). Second, while we take into account the effects of self-selection, we ignore the possibility that long commutes trigger telecommuting. We argue that whether or not increases in commuting time trigger teleworking, or teleworking triggers longer commutes is irrelevant, because it both entails a geographical expansion of labour relations. However, future research may be directed at finding instruments for *changes* in telecommuting, unrelated to changes in commuting time to assess the one-way causal effect. Finally, our fixed effects model corrects for the bias induced by preference-based sorting only to the extent that these preferences are *time-invariant*. We are hopeful that our extensive list of control variables captures remaining *changes* in these preferences, and we note that including fixed effects may at least capture more of the sorting bias than OLS models.

In line with earlier work, our results suggest that the travel savings made by working one or several days at home are not fully offset by the positive effects on commuting distance alone(Jiang 2008; Andreev et al. 2010; Zhu 2012). Beyond that, this paper stresses the effects of telecommuting on the geographical territory of labour markets. Next to reducing the labour accessibility gap between central and remote areas, telecommuting may also allow the externalities associated with the size of local labour markets, including improved searching and matching and less unfilled vacancies (Moretti 2011), to be increasingly generated across greater geographical areas, and through wider infrastructure networks (Burger and Meijers 2016). Further research may focus on the welfare effects associated with a wider geographical extent of labour markets.

Acknowledgements

This paper has benefited from a VIDI grant, with grant number 452-14-004, provided by the Netherlands Organisation for Scientific Research (NWO).

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Appendix A: Supplementary tables

Table 5 presents the summary statistics of the part of the panel for which we have valid observations for all years. Table 6 presents the regression results of the sensitivity analysis.

Table 5: Summary statistics balanced panel

Variables	N	Mean	Std. dev.	Min.	Max.
No telecommuting	2,282	0.570	0.495	0	1
Telecommuting >= 1 day/month	2,282	0.430	0.495	0	1
Telecommuting 1 day/month	2,282	0.153	0.360	0	1
Telecommuting 2 days/month	2,282	0.0916	0.289	0	1
Telecommuting 3 days/month	2,282	0.0903	0.287	0	1
Telecommuting >3 days/month	2,282	0.0951	0.293	0	1
Telecommuting weekly hours	2,282	2.926	6.933	0	97
Commuting time	2,282	26.68	21.20	0	165
Job search at t	2,282	0.0828	0.276	0	1
Job move between t-2 and t	2,282	0.0714	0.258	0	1
Job move between t and t+2	1,956	0.0573	0.232	0	1
Daily wage	2,282	111.4	38.80	10.43	391.3
Monthly wage	2,282	1,829	733.0	200	6,000
Working days/week	2,282	4.316	0.968	1	7
Firm size	2,282	564.9	2,414	0	62,000
Age	2,282	47.15	7.535	22	66
Female	2,282	0.429	0.495	0	1
Partner	2,282	0.895	0.306	0	1
Partner wage	2,282	1,240	2,757	0	75,000
Children at home	2,282	0.699	0.459	0	1
Primary education	2,282	0.0118	0.108	0	1
Basic education	2,282	0.172	0.377	0	1
Higher education	2,282	0.390	0.488	0	1
Vocational education	2,282	0.336	0.472	0	1
Bachelor degree	2,282	0.0911	0.288	0	1
Sector: Agriculture	2,282	0.00920	0.0955	0	1
Sector: Industry	2,282	0.126	0.332	0	1
Sector: Construction	2,282	0.0438	0.205	0	1
Sector: Trade	2,282	0.101	0.302	0	1
Sector: Transport	2,282	0.0609	0.239	0	1
Sector: Business services	2,282	0.135	0.341	0	1
Sector: Healthcare	2,282	0.186	0.389	0	1
Sector: Other	2,282	0.0372	0.189	0	1
Sector: Government	2,282	0.142	0.350	0	1
Sector: Education	2,282	0.159	0.365	0	1
Jobtype: Civil servant	2,282	0.270	0.444	0	1
Jobtype: Employee	2,282	0.728	0.445	0	1
Jobtype: Director	2,282	0.00219	0.0468	0	1
Jobtype: Self-employed w/ personell	2,282	0.000438	0.0209	0	1
Jobtype: Self-employed w/o personell	2,282	0	0	0	0

Table 6: Sensitivity regressions

	(1)	(2)	(3)	(4)
Telecommuting >=1 day/month	0.0572***			
	(0.0157)			
Telecommuting 1 day/month		0.0768***		
		(0.0208)		
Telecommuting 2 days/month		0.0736***		
		(0.0221)		
Telecommuting 3 days/month		0.0504**		
		(0.0219)		
Telecommuting >3 days/month		0.0360*		
		(0.0208)		
Telecommuting weekly hours			0.00373***	
			(0.000912)	
Telecommuting weekly hours 0–8				0.0459***
				(0.0164)
Telecommuting weekly hours 8–16				0.0990***
				(0.0276)
Telecommuting weekly hours 16–24				0.0663*
				(0.0397)
Telecommuting weekly hours 24–32				0.137***
				(0.0525)
Telecommuting weekly hours 32–40				0.138
				(0.109)
Telecommuting weekly hours 40+				0.202
				(0.127)
Daily wage (log)	0.147***	0.152***	0.158***	0.104***
	(0.0412)	(0.0413)	(0.0410)	(0.0342)
Firm size	3.17e-07	2.31e-07	5.36e-07	1.82e-06
	(3.57e-06)	(3.57e-06)	(3.57e-06)	(2.06e-06)
Age	-0.0188	-0.0184	-0.0167	-0.0138
	(0.0124)	(0.0124)	(0.0124)	(0.00885)
Age^2	0.000231*	0.000220*	0.000206	0.000179**
	(0.000130)	(0.000130)	(0.000129)	(8.89e-05)
Partner	0.0285	0.0323	0.0307	0.0362
	(0.0485)	(0.0485)	(0.0484)	(0.0309)
Partner wage	-1.96e-06	-2.14e-06	-2.13e-06	-1.21e-06
	(2.60e-06)	(2.60e-06)	(2.60e-06)	(9.85e-07)
Children at home	-0.0136	-0.0122	-0.00894	-0.0241
	(0.0251)	(0.0251)	(0.0251)	(0.0166)
Basic education				0.0346
				(0.0324)
Higher education,	0.0831*	0.0846*	0.0752	0.0401
	(0.0459)	(0.0459)	(0.0458)	(0.0401
Vocational education	0.143***	0.148***	0.137***	0.101**
	(0.0521)	(0.0522)	(0.0520)	(0.0473)
Bachelor degree	0.174**	0.175**	0.168**	0.146***
	(0.0692)	(0.0692)	(0.0690)	(0.0549)
Constant				0.636**
				(0.281)
Indiv. fixed effects	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Control dummies	Yes	Yes	Yes	Yes
Observations	1,489	1,489	1,489	2,266
R-squared	0.708	0.709	0.709	0.761

Notes: Robust std. errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. TC stands for telecommuting and in columns (1-2) No Telecommuting is the reference category. Control dummies include 7 working days-, 10 industry-, and 5 job type dummies.