

To what extent does working from home lead to savings in commuting time? A panel analysis using the Australian HILDA Survey

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ABSTRACT

With growing concern about the climate impact of travel, a central question is the extent to which working from home (WFH) can reduce commuting. Recently, the question has received even more attention as WFH has increased sharply with the onset of the COVID-19 pandemic. However, the state of research is marked by mixed results and lacking longitudinal evidence. We investigate the link between WFH and total weekly commuting time by applying fixed effects regression to panel data from the Australian HILDA Survey, covering the period 2002–2019. We go beyond previous research by examining the moderating roles of the extent of WFH, the duration of the WFH episode, and gender. Overall, we find that doing any work from home is associated with a significant decrease in employees' weekly commuting time of about 14% on average. The reduction sets in immediately with the start of WFH and tends to further increase thereafter. However, only high shares of WFH are associated with substantial drops in commuting time, and reductions are larger for women than men. Taking into account Australian workers' reported WFH preferences, our results suggest maximum potential future commuting time savings of about 17–25% compared to 2019.

1. Introduction

As early as the 1970s, researchers expressed the hope that working from home (WFH) could reduce commuting and thus lower congestion, pollution, and energy consumption (Nilles et al., 1976; Harkness, 1977). Nevertheless, global CO₂ emissions from the transport sector have risen sharply over the past two decades, with passenger cars contributing by far the most in absolute terms (IEA, 2021). At the same time, commuter traffic accounts for a significant share of total traffic in many countries (e.g. U. S. Department of Transportation, 2017; Eurostat, 2021). A reduction in commuter traffic could therefore contribute to a significant reduction in emissions.

More recently, the COVID-19 pandemic has shown impressively that work lives can change rapidly. Whereas previously WFH was practiced rather rarely – although there were clear differences between countries (e.g. Messenger, 2019) – the pandemic led to a sharp increase in the prevalence of this work mode. For example, based on averaged data from eight OECD countries, the share of workers WFH increased from 16 % before the pandemic to 37 % in March 2020 (OECD, 2021). As

WFH is expected to remain an important phenomenon beyond the COVID-19-period (e.g. Buomprisco et al., 2021; Salon et al., 2022), the long-standing question of whether WFH can reduce commuting has received even more attention.

The simple assumption is that WFH reduces overall commuting because it allows workers to reduce the number of trips to the workplace (i.e. the frequency of commuting). However, the current state of research is inconclusive. While earlier studies in particular suggest that WFH leads – at least in the short term – to a reduction in total distance travelled to work (for a review, see Andreev et al., 2010), other research shows that home workers commute longer one-way distances than their non-WFH counterparts (Helminen and Ristimäki, 2007; Zhu, 2013; Melo and de Abreu e Silva, 2017).

In general, the existing research on this topic has a number of limitations. First, it relies mainly on cross-sectional data and lacks longitudinal studies (Allen et al., 2015), with the exception of the studies by de Vos et al., (2018; 2019) and Faber et al. (2023). This means that conclusions regarding causality are uncertain due to bias from unobserved heterogeneity, such as selection with respect to ambition, ability, and

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residential or mobility preferences (de Graaff, 2004; Wang et al., 2023). There are arguments that effects of WFH on commuting can be biased upwards or downwards in simple cross-sectional studies (de Vos et al., 2018). On the one hand, telecommuters may have stronger preferences for shorter commutes. On the other hand, there might be a bias of residential sorting, e.g. individuals living in certain areas may have longer commutes and stronger preferences for telecommuting. Furthermore, those who are more ambitious may have both a higher willingness to commute and a higher likelihood of doing additional work from home. A few studies use instrumental variable approaches to deal with issues of omitted variables and reverse causality (Jiang, 2008; Zhu, 2012; Zhu and Mason, 2014); however, these also produce mixed findings (cf. de Vos et al., 2018, p. 379).

Second, different measures for WFH and commuting make it difficult to compare the results across studies (cf. Andreev et al., 2010; Elldér, 2020). In this context, the panel study by de Vos et al. (2018) uses one-way commuting time, which has the drawback that it does not allow predicting the impact of WFH on total commuting time (e.g. per week). This is because employees may use WFH to work further away from home, effectively increasing their daily commuting time, while their average weekly commuting time remains unchanged or may even decrease if the frequency of commuting is simultaneously reduced.

Third, few studies focus on whether the extent of WFH and gender moderate the effect of WFH on commuting times and whether the effect changes over time, i.e. whether it is short-term or persists over longer periods (Allen et al., 2015). For example, the panel study by Faber et al. (2023) examined the linear effect of weekly hours worked from home on commuting time, the latter measured during a 3-day observation period, without accounting for potential heterogeneity in the effect with respect to the extent of WFH and gender. To the best of our knowledge, only one study (Pablonia and Vernon, 2022) has investigated the association between the extent of WFH and commuting for men and women separately. Given the marked gender differences in mobility behaviour and WFH use (e.g. Crane, 2007; Powell and Craig, 2015), this seems an important shortcoming.

The present paper adds to the literature in several ways. First, our study draws on panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, covering the period 2002–2019. We apply fixed effects (FE) panel regression models (e.g. Brüderl and Ludwig, 2015) to this data to examine how within-person *changes* in WFH are associated with *changes* in commuting time. Compared to cross-sectional analysis, these models allow for a clearer interpretation in terms of causal inference by implicitly controlling for all time-constant unobserved characteristics (e.g. residential and commuting preferences). Second, we consider WFH as dichotomous indicator as well as the share of time worked from home per week to take into account possible effect differences in terms of the extent of WFH. Our outcome variable represents total weekly commuting time, which has been described as “ideal” and preferable to one-way commutes (Zhu, 2012; Melo and de Abreu e Silva, 2017), as it captures other aspects of commuting, such as frequency and timing, in addition to duration/distance of the single commute, which is important to assess the impact on total commuting time. Third, our study examines whether the effect of WFH on commuting time differs by gender, considering the clear gender differences in mobility behaviour and WFH use. Fourth, we are the first in this field to estimate FE models with impact functions (e.g. Ludwig and Brüderl, 2021) that allow investigating how the effect of WFH on commuting time evolves over the course of the home working episode. Overall, the HILDA Survey data offers unique advantages in terms of design, representativeness, sample size, variables on WFH and commuting, and relevant control variables.

Australia is an interesting case study for several reasons. The sheer size of the country and the large distances between its major cities suggests that bridging spatial distances is of crucial importance in Australia. Pre-pandemic commuting times were long and increasing over time. Over the 2002–2017 period alone, Australia saw a 23 %

increase in average daily commuting times from 49 min to one hour. Over the same period, the share of workers with long daily commutes of two hours or more increased from 12 to 18 %. Commuting times are particularly long in the most densely populated areas and among men (Wilkins et al., 2019). Finally, Australia stands out as one of very few countries that provides specific groups of workers with the right to request flexible work arrangements, including WFH (OECD, 2021). This right has been established with the Fair Work Act 2009 and relates to (non-casual) employees who have worked for their employer for at least 12 months and who, for example, have parenting or caring responsibilities, have a disability, or are older than 54 years. However, employers can refuse such request on reasonable business grounds. Overall, about 25 % of Australian workers aged 18 to 64 years reported usually doing some work from home in 2019 (based on HILDA Survey data). Even higher levels of WFH can be expected in Australia after COVID-19. Recent surveys – like the University of Melbourne’s Taking the Pulse of the Nation Survey (Petrie, 2022) and Boston Consulting Group’s Workforce Sentiment Survey (Mattey et al., 2020) – show that many Australian workers would like to continue to work (at least a part of their time) from home.

2. Literature review, theoretical considerations and hypotheses

In this study, we use the term WFH as a synonym for telework, which is understood to mean all work performed in paid employment that is done at home away from the workplace, usually using Information and Communication Technologies (ICT) (Nilles, 1988). In theoretical terms, we assume that work life is organised around home and work location, and the two are linked by commuting distance, where commuting can be viewed as a cost (e.g. travel expenses, stress, limited time for family and leisure) (Kalter, 1994; Rouwendal and Rietveld, 1994; Abraham and Nisic, 2007).

2.1. The effect of working from home on commuting time

Building on Salomon (1985), four theoretical mechanisms in the relationship between WFH and commuting can be differentiated: *Substitution* means that WFH leads to a reduction in commuting; *complementarity* implies that WFH generates further commuting; *modification* means that WFH leads to a change in commuting behaviour; and *neutrality* suggests that WFH does not lead to any effects on commuting behaviour.

In terms of *substitution*, WFH can reduce travel between work and home when the number of trips to the workplace (i.e. the weekly commute frequency) is reduced (Andreev et al., 2010; Allen et al., 2015; de Abreu e Silva and Melo, 2018a). Moreover, people with long commutes should be more inclined to WFH, since for them the savings due to the omitted commutes are particularly high (e.g. Helminen and Ristimäki, 2007; Zhu, 2013; Mergener and Mansfeld, 2021), and WFH is often considered a strategy for coping with longer and more expensive commuting trips, at least in the short term (de Abreu e Silva and Melo, 2018b).

However, based on search theory, individuals can be expected to constantly search for new jobs and/or dwellings to maximise wages and place utility (Devine and Kiefer, 1993; van Ommeren et al., 1999). Since WFH can reduce commuting costs, it enables persons to widen their search radius, which increases the accessible number of more valuable jobs and better dwellings (e.g. Sjaastad, 1962; So et al., 2001; Manning, 2003). Thus, WFH can dissolve the strong ties between place of residence and employer’s premises, so that employees no longer attach as much importance to living close to their place of work (e.g. DLR, 2021). Individuals may be willing to accept longer one-way commutes in favour of a better job or dwelling knowing that they can reduce commuting times by WFH if necessary (e.g. Muhammed et al., 2007; de Abreu e Silva and Melo, 2018b). This could indicate a *complementarity* effect, where the reduced number of trips is (more than) offset by longer one-way

commuting distances (e.g. Ravalet and Rérat, 2019).

WFH could also result in a *modification* of commuting patterns with commuting being shifted to off-peak hours (Andreev et al., 2010; Huang et al., 2023). This, in turn, could lead to a (small) reduction in commuting time due to lower traffic volumes. In this regard, studies show that employees who do not WFH on a full-day basis are more likely to commute off-peak (Glogger et al., 2008; Asgari and Jin, 2018). In addition, car use and the use of active transportation modes seem to increase with WFH (de Abreu e Silva and Melo, 2018a; Elldér, 2020), which also represents a modification of commuting patterns that could affect commuting time.

WFH could also be used for reasons other than to reduce commuting time. In particular, WFH could be deployed to perform additional work from home, e.g., in the evenings or on weekends. Telework has repeatedly been shown to be associated with longer working hours (Glass and Noonan, 2016; Gschwind and Vargas, 2019). In terms of *neutrality*, this could mean that WFH has no impact on commuting behaviour. If, however, by doing the extra work from home, commuting is increased at peak instead of off-peak times, this could have a complementary effect and increase commuting time (de Graaff, 2004).

Further and updated empirical research is needed to gain insights into the relationships between WFH and commuting, as previous studies do not provide a clear picture (cf. Elldér, 2020). In their literature review of fairly early studies, with the majority conducted before the year 2000, Andreev et al. (2010) concluded that, in the short term, WFH leads to a (small) reduction in distance travelled to work. For instance, a U.S. study shows that the reduction in annual vehicle miles travelled due to telecommuting was 0.8 % or less (Choo et al., 2005). Mokhtarian et al. (2004) also find teleworkers' total commuting to be shorter compared to non-teleworkers, even if teleworkers have longer company-home distances. Likewise, other recent studies find substitution effects in the form of reduced travel (Lachapelle et al., 2018; Elldér, 2020; Faber et al., 2023).

By contrast, some recent studies found complementarity effects (i.e. WFH generates additional commuting) (cf. Elldér, 2020). For instance, de Abreu e Silva and Melo (2018b) showed a positive association of telework frequency with weekly commuting distance travelled, although the association between telework and the number of commuting trips was negative. Using panel data from Dutch workers, de Vos et al. (2018) found that telecommuting was associated with 5 % longer one-way commuting times. Similarly, a recent study by Motte-Baumvol and Schwanen (2024), using cross-sectional data, found that teleworkers in the UK had longer commuting times despite commuting fewer days than other workers, which was mainly due to different commuting patterns (e.g. commuting by train and/or working in a congested area).

Overall, considering the theoretical arguments and empirical evidence, WFH and commuting appear to be substitutes – although not perfect ones, and savings in commuting may turn out to be lower than expected. Therefore, we put forward our first hypothesis:

H1a: Working from home is associated with a small reduction in weekly commuting time.

Following the theoretical arguments above, a crucial moderating factor is the extent of WFH. If only a small share of time is worked from home, complementarity and neutrality effects should dominate. For example, a low WFH extent may result from employees simply bringing additional work home, while still commuting on a daily basis. In addition, longer one-way commuting distances could be less effectively compensated if commuting trips are only rarely saved. However, relatively few studies have examined the moderating effect of the extent of WFH on the relationship between WFH and commuting. Most of these suggest that overall commuting time savings are larger for those who work from home to a greater extent (e.g. Melo and de Abreu e Silva, 2017; Lachapelle et al., 2018; Elldér, 2020; Caldarola and Sorrell, 2022; Pablonia and Vernon, 2022). For instance, according to a British study (Melo and de Abreu e Silva, 2017), a significant reduction in weekly

commute time is only achieved with a teleworking extent of 3 + days/week. Overall, our theoretical considerations and the existing empirical findings suggest that the extent of WFH moderates the effect on commuting time: A small share of total working time done from home might not yield any savings in commute time, but there might be a “tipping point” at a greater extent beyond which commute time is greatly reduced. Therefore, we put forward our second hypothesis:

H2a: Only a large extent of WFH will result in a substantial reduction in weekly commuting time.

2.2. The role of gender differences in WFH and commuting

Since mobility behaviour, including WFH, is gender-specific, we expect differences for female and male employees regarding the link between WFH and commuting. Research has repeatedly shown that women have shorter commutes than men (e.g. Crane, 2007; Wilkins et al., 2019; Skora et al., 2020). Following the Household Responsibility Hypothesis (e.g. Turner and Niemeier, 1997; Gimenez-Nadal and Molina, 2016), mobility differences are primarily explained by prevailing traditional gender roles. Men are more likely to be main breadwinners and more focused on their employment careers. Women, by contrast, more often act as secondary earners on a part-time basis and take on more responsibility for household tasks and unpaid care work (e.g. Altintas and Sullivan, 2016; Pailhé et al., 2021). Given this gendered labour division, women are more limited in time and space than men (Nisic, 2017). This is reflected in women's shorter commutes, as it is more important for them to choose a job close to home to take care of other obligations on short notice, such as running errands or dropping off and picking up children, if needed (McGuckin et al., 2005). Moreover, the cost-benefit ratio of commuting is worse for women than for men, as commuting is typically associated with monetary costs due to travel expenses (van Ommeren and Fosgerau, 2009), whereas earnings are usually lower among secondary earners. In addition, long commutes can lead to travel-related stress, especially for women (e.g. Rüger et al., 2017), and limit available time that could be used for household responsibilities, resulting in higher opportunity costs for women (e.g. Van den Berg and Gorter, 1997; Rouwendal and Nijkamp, 2004).

Thus, WFH to save valuable time by reducing commuting should be more important for women than men. This notion is corroborated by previous research elucidating that the use of WFH seems to be characterised by traditional gender roles. While women tend to use WFH for combining work and private life, or to even spend more time on domestic work and childcare (Powell and Craig, 2015), men do not primarily consider WFH to better meet private demands (Sullivan and Lewis, 2001). By contrast, studies suggest that men are more likely to use telework to enhance their work performance, leading to working longer hours and during leisure time to meet work demands (e.g. Glass and Noonan, 2016; Eurofound and the International Labour Office, 2017). Thus, men appear to use WFH more often to perform additional work (e.g. in the evening) rather than to replace regular office hours with WFH. By this, no savings in commuting time can be expected. Moreover, men with a small extent of WFH commute longer distances than men who do not WFH at all, while this is not the case for women (Mergener and Mansfeld, 2021). Thus, only when a large part of the working time is spent at home, a reduction in the total commuting time can also be expected for men. These considerations suggest that gender moderates the effect of (the extent of) WFH on commuting time and lead us to the following hypothesis:

H1b: Overall, WFH is associated with a stronger reduction in weekly commuting time among women than men.

H2b: For women, a reduction in weekly commuting time can also be observed with a smaller extent of WFH compared to men.

2.3. Variations over time in the effect of working from home on commuting time

To our knowledge, no research so far has examined how the effect of WFH on commute time evolves over the course of the home working episode (for a general argument in favour of more research on the role of time in relation to WFH using longitudinal data, see [Allen et al., 2015](#)). In principle, the effect could occur immediately with the onset of WFH or later, and it could be stable, increasing or decreasing over time as the worker maintains WFH. Therefore, the dynamics of commuting trajectories over the course of the WFH episode could reveal more about the nature of the relationship between WFH and commuting and the potential underlying mechanisms.

As discussed earlier, WFH may be an incentive for longer one-way commutes by expanding the search radius for residences and/or work locations or by reducing residential relocations closer to the workplace (e.g. [Muhammed et al., 2007](#); [de Vos et al., 2018](#); [Ravalet and Rérat, 2019](#)). Changing residences and/or work locations could therefore be processes that might offset the commuting time saved by WFH in the long run. This would suggest that a potential negative effect of WFH on commuting time decreases or even turns positive over the course of the home working episode. However, most existing studies suggest no or only a small counteracting effect by changes of residences and/or work locations ([Ettema, 2010](#); [Kim, 2016](#); [Muhammed et al., 2007](#); [Ory and Mokhtarian, 2006](#); but see [Ory and Mokhtarian, 2005](#)). Thus, a clear tendency for workers to trade off lower commuting frequency for longer commuting distances over time cannot be identified based on their relocation behaviour.

Following another line of reasoning, commuting time can be expected to continue to decrease over time as workers (are able to) expand their share of WFH for several reasons: First, as the duration of the WFH experience increases, trust builds between employers and employees, which appears to be a key factor in successful work and good performance at home ([Kim et al., 2021](#)) and allows employees to increase their share of time WFH ([Golden, 2006](#)). However, building trust takes time, which is why a common strategy is to initially introduce WFH as a test or trial for a period of time ([Beauregard et al., 2019](#)). If the employer's trust and expectations are met, it can be assumed that employees will (be allowed to) continue to use WFH and also extend their share of time WFH ([Kaplan et al., 2018](#)). Second, WFH can also present challenges for employees when they start using it, as specific competencies are required to be productive at home, e.g. self-discipline, self-motivation, ability to work alone, and time management skills ([Baruch, 2000](#)). Such competencies can be acquired with increasing experience with WFH. Thus, it can be assumed that WFH becomes more attractive with increasing experience, which is why employees then also extend their share of time WFH over time. Third, being productive when WFH also depends on the physical set-up at home, e.g. the technological infrastructure and furniture. If employees enjoy WFH and receive support for it from their employers, it can be assumed that they will equip their offices at home better and more professionally over time ([Gajendran and Harrison, 2007](#); [Scott et al., 2012](#); [Carillo et al., 2021](#)). Thus, working in an increasingly well-equipped and optimised work environment may lead to an increase in the share of time WFH over time.

Home workers may not only be able to optimise their work environment but also the rhythm of everyday life with continued WFH. They may increasingly optimise their commuting behaviour, for example, by commuting at off-peak times, which may lead to further savings in commuting time. Furthermore, it may take some time for all household members to adjust to a new pattern of working time, household chores and family time after someone in the household starts WFH. Again, this suggests that the home worker may be able to extend the share of WFH over time, leading to additional commuting time savings.

Based on these considerations, we put forward our third hypothesis:

H3: The negative effect of working from home on weekly commuting time further increases over time.

3. Data and methods

3.1. Data

We draw on data for the period 2002 to 2019 from Release 19 of the Household, Income and Labour Dynamics in Australia (HILDA) Survey ([Department of Social Services and Melbourne Institute of Applied Economic and Social Research, 2020](#)). The HILDA Survey is an annual household panel study first conducted in 2001 that captures a representative sample of households in Australia ([Watson and Wooden, 2021](#)). We restrict the sample to employees aged 16 to 64 years with at least 10 working hours per week ($n = 135,365$ observations). For reasons of plausibility, we exclude observations where workers report a commuting time of zero but at the same time work less than 95 % of their time from home ($n = 1,791$). After also excluding cases with missing values ($n = 21,377$), our sample comprises 112,197 observations from 18,803 individuals.

3.2. Measures

As dependent variable we use the logarithmised total weekly commuting time in hours and minutes. This information was collected via a question asking workers to report the time they spend travelling to and from a place of paid employment in a typical week. In this regard, total weekly commuting time has been described as an "ideal" measure ([Zhu, 2012](#); [Melo and de Abreu e Silva, 2017](#)), as it simultaneously captures several aspects of commuting, such as frequency, timing, and duration/distance of the single commute. As we used the natural logarithm of weekly commuting time to approximate a normal distribution, all observations with zero commuting time were assigned a value of 0.001 h to be included in the analysis.

As central independent variables we draw on the question "In your main job, are any of your usual working hours worked at your home (that is, the address of your usual place of residence)?" to create a dichotomous indicator for WFH and the question "Approximately how many hours each week do you usually work at home?" to operationalise the extent of WFH. We divide the number of hours usually worked from home by the total number of working hours in the main job to generate a measure of the share of time worked from home. In order to test for non-linear effects, we categorise this share of time as 0 %, 1–19 %, 20–39 %, 40–59 %, 60–79 % and 80–100 %.

In order to adjust for general shifts in commuting times, we control for survey year in all models. In a second specification, we add worker- and job-related control variables, broadly following [de Vos et al. \(2018\)](#). In terms of worker characteristics, we consider the presence of a partner or children in the household, the weekly wage of the partner (deflated using the wage price index; [Australian Bureau of Statistics, 2021](#)), the educational level, the labour market experience (as measured by years in paid work in a quadratic specification) as well as the region of residence (differentiating between major cities, inner regional areas, and more remote areas). In terms of job characteristics, we account for the daily wage (deflated) and weekly working hours in the main job, occupation, industry and firm size. Given our commuting time measure relates to entire working weeks rather than individual trips, we also control for the number of working days in the main job. Finally, we include an indicator for multiple job holders as the commuting time measure reflects time spent travelling to and from all jobs, whereas the information on WFH relates to the main job only. Frequencies for all variables in the sample (except survey year) are presented in [Table A1](#) in the [appendix](#).

3.3. Methods

To investigate how WFH impacts on weekly commuting time we use fixed-effects (FE) panel regression models (e.g. [Brüderl and Ludwig, 2015](#)). These models implicitly control for time-invariant unobserved individual characteristics, because they use only within-person variance

over time. Consequently, time-constant characteristics that may affect both the likelihood of WFH and commuting time, such as ambition, ability, residential or mobility preferences, are accounted for. This means we come closer to identifying the causal link between WFH and commuting time.

A potential limitation of FE regression is that low variance in key variables may result in limited external validity, as the findings may only apply to a selected subset of respondents (Hill et al., 2020). However, background analyses show that in our case the extent to which individuals work from home is very variable. The share of workers in the sample who are observed changing between any of the six (0 % up to 80–100 %) categories over the course of the study is around 27 % overall. This is because most people never work from home (since most jobs actually cannot be done from home, e.g. Sostero et al., 2020). Among those individuals who did work from home at any point in time, 88 % changed categories. These “changers” account for 94 % of the observations in the WFH categories between 1–19 % and 80–100 %. In Table A2 we present the characteristics of workers who are observed changing between WFH categories, separately by WFH category (with some categories combined to save space).

In addition, we use FE models with impact functions (Ludwig and Brüderl, 2021) that help us understand how the effect of WFH on commuting is distributed over time (i.e. changes after the onset of WFH). We constructed a variable counting the number of years that have passed since entry into WFH, with periods longer than ten years grouped together. All time points prior to entry into WFH serve as reference. The results presented in this study were estimated using the command ‘xtreg’ in Stata 16 with standard errors clustered on the individual level.

To examine the effect of WFH on commuting time, we estimate three sets of models: First, we investigate the overall effect of WFH on commuting time using a binary indicator for home working. Second, we analyse the effect of WFH in more detail by looking at the share of time worked from home. For these steps, we analyse separate models by gender and formally test for gender differences by running models with an interaction term for WFH and being female. Third, we use impact function FE models to analyse how the effect of WFH on commuting time varies over time. In addition, we combine the results of our FE models with the findings from recent surveys on Australian workers’ stated preferences regarding future WFH patterns (Mattey et al., 2020; Petrie, 2022) to provide insights for policy on how much commuting time could potentially be saved in the future through WFH if workers’ stated preferences were accommodated.

4. Results

4.1. Overall effect

Panel A in Table 1 presents results from the analysis of the binary measure, indicating whether workers do or do not work any of their usual hours from home, for the pooled sample and separately for female and male workers. In a base model, we only controlled for survey year, and in an extended model, we included all other control variables. In order to conserve space, only the coefficients of interest are reported; however, the full models can be found in Appendix Table A3. Almost across the board, doing any work from home in a usual week was associated with a significant decrease in commuting time. For example, the coefficient of -0.092 in the base model for the pooled sample reflects about a 9 % reduction in commuting time (calculated as $100 \cdot (\exp(\beta) - 1)$). Furthermore, in all cases, the effect was larger in the extended compared to the base model, suggesting that individuals working from home have job and personal characteristics associated with lengthy commutes. For example, the coefficient of -0.149 in the extended model for the pooled sample reflects about a 14 % reduction in commuting time. We also formally tested for gender differences by re-running the models with an interaction term for WFH and being female. The interaction term was sizable and statistically significant ($b_{\text{base}} = -0.138$, $p \leq 0.01$; $b_{\text{extended}} = -0.152$, $p \leq 0.01$), suggesting that WFH was associated with larger reductions in commuting time among female compared to male home workers.

Panel B of Table 1 presents results from models considering the extent of WFH in the form of the share of hours worked from home as a percentage of total working hours (estimates of control variables not reported but very similar to those presented in Table A3). The base model showed a non-linear relationship between the share of time worked from home and weekly commuting time: Relatively low shares of WFH (below 40 % for the pooled sample as well as for men and below 20 % for women) were associated with significantly longer commutes compared to workers not WFH at all, whereas higher shares were associated with shorter commutes compared to those not WFH. In the extended model, the positive coefficients for the lower categories attenuated, but the positive association of working 20–39 % of the time from home among men remained significant. Among both genders, the significant negative associations for the two highest categories remained statistically significant and similar in size in the extended model. Overall, the reduction in commuting time was much larger in the top category than in the other categories. For example, the coefficients in the extended model for all workers designated a 32 % decrease in commuting time for those working 60–79 % from home but a 98 % decrease for those working at least 80 % from home. A formal test for

Table 1
Working from home and (ln) weekly commuting time: Results from fixed-effects regression (b-coefficients).

	(1)	(2)	(3)	(4)	(5)	(6)
	All base model	All extended model	Men base model	Men extended model	Women base model	Women extended model
Panel A: Doing any work from home (ref. = no)						
Works from home	-0.092^{**}	-0.149^{**}	-0.022	-0.063^{**}	-0.158^{**}	-0.229^{**}
n(observations)	112,197	112,197	55,603	55,603	56,594	56,594
adj. within- R^2	0.012	0.060	0.014	0.053	0.011	0.073
Panel B: Share of time worked from home (%; ref. = none)						
1–19	0.065^{**}	0.005	0.058^{**}	0.017	0.074^{**}	-0.007
20–39	0.063^{**}	0.015	0.103^{**}	0.058^*	0.038	-0.013
40–59	-0.040	-0.064^+	0.075	0.046	-0.110^*	-0.128^{**}
60–79	-0.396^{**}	-0.388^{**}	-0.359^{**}	-0.351^{**}	-0.396^{**}	-0.383^{**}
80–100	-3.909^{**}	-3.889^{**}	-3.371^{**}	-3.358^{**}	-4.193^{**}	-4.151^{**}
n(observations)	112,134	112,134	55,580	55,580	56,554	56,554
adj. within- R^2	0.105	0.149	0.069	0.107	0.135	0.188

Notes: **, * and + denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively. The base models are adjusted for survey year, the extended models additionally control for worker and job-related characteristics (see Methods section and Table A3).

gender differences in the form of an interaction model revealed that the effects of a WFH share of 20–39 % ($b_{\text{extended}} = -0.063$, $p = 0.070$), 40–59 % ($b_{\text{extended}} = -0.180$, $p = 0.007$) and 80–100 % ($b_{\text{extended}} = -0.811$, $p = 0.039$) differed significantly between men and women, indicating that commuting time savings were notably larger for women than men even when WFH to a similar extent.

4.2. Variations in the effect over time

Fig. 1 presents results from FE regression with impact functions. It shows a marked and significant drop in commuting time of around 10 % in the first year after starting WFH compared to the years before WFH. For workers who continued WFH, commuting time decreased further over time.

Separate analyses by gender (results not shown) revealed that this pattern was particularly marked for women. Furthermore, background analyses showed that the decrease in commuting time was partly due to workers extending their share of time WFH over time, with the average share of time worked from home increasing from 15.2 % in year 1 to 25.1 % in year 9. Another relevant factor appeared to be selection, as those who eventually ended up WFH for a long period already started out with slightly higher shares of time WFH. Precisely, those who ended up WFH for five years or less started out with an average WFH share of 15.0 % in year 1, whereas those who ended up WFH for six years or more started out with an average WFH share of 17.9 %. However, in both groups, the share of time WFH increased over the years.

Additionally, we analysed the effects of exiting WFH on commuting time (results not shown). The findings complemented those for entry into home working: Exit from WFH resulted in a significant initial increase in commuting time of around 12 % ($b_{\text{extended}} = 0.112$, $p \leq 0.01$), followed by very modest further increases over time.

4.3. Possible post-COVID-19 commuting scenarios: Tentative projections

Several recent surveys showed that many Australian workers would like to continue to work (at least part of their time) from home (e.g. Matthey et al., 2020; Beck and Hensher, 2021; Petrie, 2022). Combining our estimates with the findings from these surveys can provide tentative insights for policy into how much commuting time could be saved in the future through WFH on a national level if employees' preferences were accommodated. Using workers' stated preferences for our projections means that the scenarios presented likely show the maximum potential

savings in weekly commuting time in a 'what if' scenario. In this context, it should be noted that preferences which are stated in hypothetical form in surveys may differ from revealed preferences. That is, even when given the choice to work from home as much as they want, some of those workers who stated a preference for extensive WFH may still end up WFH less often. This could be, for example, because they miss the face-to-face contact with co-workers, are disturbed by others when WFH, or are less productive when WFH. Overall, the realisation of preferences depends on a number of factors (e.g. Mokhtarian and Salomon, 1994). Table 2 provides information from two representative surveys, the University of Melbourne's Taking the Pulse of the Nation Survey (TTPN, Petrie, 2022) and the Boston Consulting Group's Workforce Sentiment Survey (WSS, Matthey et al., 2020), and links these to our estimates.

In the data from three periods of the TTPN Survey (April 2021, September/October 2021 and January 2022, $N = 7,200$ from a total of six survey rounds), close to half (49 %) of employed respondents could not or would not want to work from home at all. Among the remaining workers, a large share (24 %) responded that they would like to work from home between 80 and 100 % of the time, while smaller shares would like to work some of their time from home but less than 80 %. Compared to the actual distribution among employees in the HILDA Survey in 2019, the realisation of this scenario would entail a decline of the share of workers not WFH (–33 percentage points) and WFH less than 20 % of their time (–6 percentage points), and an increase in the categories with a higher WFH share, particularly the 80–100 % category (+22 percentage points). We have then combined (i.e., multiplied) these increases/decreases with our estimated differences in weekly commuting time between home workers in these categories and workers not WFH from the extended model for all workers in Table 1 to gauge overall changes in weekly commuting time on a national level. For example, combining the 22 percentage points influx into the WFH category of 80–100 % with the estimated reduction in commuting time of 98 % for every worker who changes into this category from not WFH would result in about a 21.9 % reduction in overall commuting time ($[22.4 \cdot -98.0] / 100$). Evidently, the validity of this extrapolation is based on the assumption that future home workers would behave similarly in terms of commuting patterns to the home workers that our FE regression analysis is based on. Under this assumption, we would see an overall decline in commuting times of close to 25 %, if future employees were to work according to the pattern indicated in the TTPN. This decline would largely be driven by the large increase in the share of workers in the 80–100 % category. A similar conclusion would be reached if we based

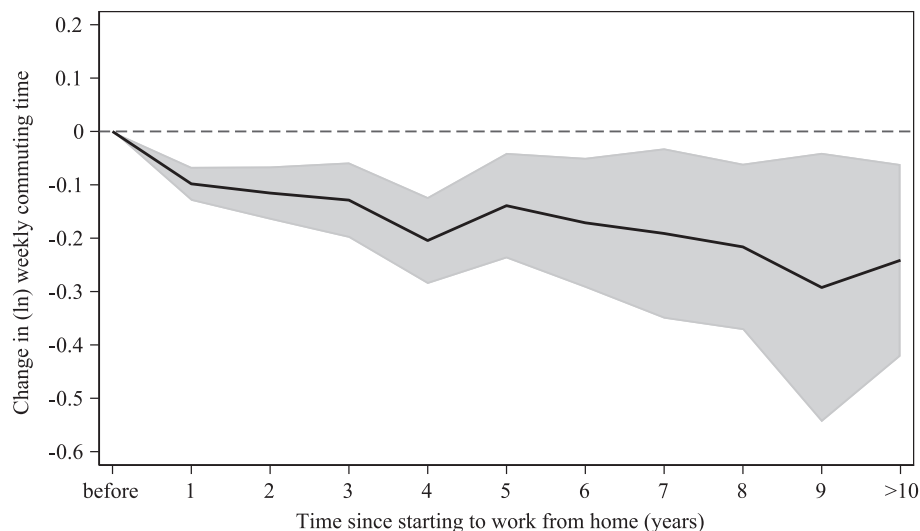


Fig. 1. Changes in (ln) weekly commuting time since starting WFH: Estimates from impact function FE model, 95 % confidence intervals. Notes: $N = 104,912$. Control variables as in the extended model in Table 1 (except survey year grouped in five periods instead of single years). Each “year category” consists of at least 119 cases (in year 9) up to 6,085 cases (in the 1-year category).

Table 2

Projections of future weekly commuting time savings based on worker preferences for post-COVID WFH.

Share WFH (%)	Actual 2019	Desired post-COVID-19		Difference actual and desired		Estimates ^a	Savings in commuting time	
	HILDA	TTPN	WSS	TTPN	WSS	HILDA	TTPN	WSS
None	81.3	48.5	40.0	-32.8	-41.3		0.0	0.0
<20	9.8	4.0	8.0	-5.8	-1.8	0.5	0.0	0.0
20–39	6.0	7.1	11.0	1.2	5.0	1.5	0.0	0.1
40–59	1.4	9.4	17.0	8.1	15.6	-6.2	-0.5	-1.0
60–79	0.5	7.5	9.0	7.0	8.5	-32.1	-2.2	-2.7
80–100	1.1	23.5	15.0	22.4	13.9	-98.0	-21.9	-13.6
Total	100.0	100.0	100.0				-24.7	-17.3

Notes: Actual distribution in 2019 based on weighted data for employees aged 16–64 years in the HILDA Survey. TTPN Survey and WSS data based on all adult workers. Original WSS categories were slightly different (1–20 %, 21–40 %, 41–60 %, 61–80 %, 81–100 %). ^a Estimates taken from the extended model for all workers in Panel B, Table 1, calculated as $100 \times (\exp(b) - 1)$.

our assumptions on the survey data presented in Beck and Hensher (2021), where the overall pattern of desired post-COVID home working patterns is similar to TTPN.

By contrast, respondents in the WSS (conducted in May 2020, N = 1,002) did not show an equally strong preference towards exclusive WFH as the TTPN or Beck & Hensher survey respondents. Only 15 % regard it as ideal to work from home for more than 80 % of their working time. Instead, larger shares chose the middle categories of working between 1 and 80 % of the time from home. Compared to the actual distribution in 2019, realisation of this scenario would yield the biggest increase of workers in the 40–60 % category (+16 percentage points). However, based on our estimates, this category would only be associated with a 6 % reduction in commuting time compared to the “none” category. Consequently, a future working pattern along the lines of the preferences stated in the WSS would result in much smaller commuting time savings, amounting to about 17 % overall.

4.4. Further analyses

We re-ran the extended models of Table 1 with several modifications (key results can be found in Appendix Table A4). First, we excluded multiple job holders given the information on WFH related to the main job, whereas information on commuting time related to all jobs. The results were similar to the main models, but the negative coefficients pertaining to large WFH shares became larger.

Second, we sought potential explanations for the finding that the association between working 20–39 % of the time from home and commuting time remained positive in the extended model for men ($b = 0.058$, see Table 1, model 4). Further analyses showed that there were five industry subdivisions (based on the 2-digit Australian and New Zealand Standard Industrial Classification) in particular that contributed to this effect: Finance, Public Administration, Administrative Services (e.g., Travel Agency and Tour Arrangement Services), Food and Beverage Service, and Building Construction. Upon exclusion of these industries, the weak positive effect disappeared almost entirely. We can only speculate as to why some workers in these industries experience longer commutes when working in hybrid arrangements. What these industries could potentially have in common is a relatively high share of employees with intensive work-related travel (e.g. business trips, on-site customer service). Since in the HILDA Survey, commuting time was collected as “time spent travelling to and from a place of paid employment” (see Data and methods section), some employees in these industries may have understood this to refer (also) to their work-related travel (cf. Caldarola and Sorrell, 2022). Studies have shown a strong positive association between WFH and work-related travel (e.g. Zhu and Mason, 2014; Caldarola and Sorrell, 2022). However, if we recalculate our predictions from Table 2 excluding these industries, the results are practically identical. All in all, despite some workers potentially including work-related travel in their estimate of commuting time, this issue appears to be minor and the measurement of commuting in the

HILDA Survey can be considered valid: It provides results that are comparable to other surveys, for example in terms of commuting trip duration (Bureau of Infrastructure, Transport and Regional Economics, 2016).

Third, we analysed the association between WFH changes and commuting time changes that happen while working for the same employer. This way, we cancelled out the effect of changes in WFH patterns and commuting time that co-occur with a job change. Overall, the results are very similar to the main model, although WFH appeared to be associated with slightly greater commuting time savings for hybrid work arrangements. For example, in the model for all workers, the coefficient of the 40–59 % WFH category ($b = -0.109$) is more negative than in the corresponding main model ($b = -0.064$), and among men, the positive coefficient for the 20–39 % category from the main model ($b = 0.058$) was practically reduced to zero ($b = 0.013$). One explanation could be that the mechanism of switching to a new job that allows (more) WFH and at the same time is further away from home is no longer in play. This mechanism would represent a complementarity effect in which the reduced number of trips is offset by longer one-way commuting distances.

Fourth, we attempted to gauge the relevance of unobserved heterogeneity by comparing the results from our FE models to pooled OLS models, where the sample in the OLS models was restricted to workers changing WFH category to ensure comparability. The results showed that for low or medium shares of WFH (up to 79 %), positive coefficients were larger and negative coefficients were smaller in the OLS model compared to the FE model (with most of these differences being quite substantial), suggesting these workers have unobserved traits connected with longer commutes. For example, while the coefficient in the extended FE model for all workers indicated a 32 % reduction in commuting time for those working 60–79 % from home ($b = -0.388$), this reduction amounted to only 17 % in the pooled OLS model ($b = -0.189$). By contrast, the negative coefficient of the topmost category was slightly larger in the pooled OLS model, indicating this group has unobserved traits related to shorter commutes. Use of the pooled OLS estimates instead of the FE estimates for the tentative projections in Table 2 would therefore result in markedly smaller overall commuting time savings, e.g. 14 % instead of 17 % when using the WSS data.

Fifth, we used the number of hours usually worked from home (rather than the share) as the measure for the extent of WFH. The results were similar to those from the models using the share of time worked from home. However, the link between the extent of WFH and commuting time was more linear for men, that is, there was no positive association between WFH relatively few hours and commuting time.

Sixth, we used the daily commuting time (rather than the weekly commuting time) as dependent variable (Appendix Table A5). Following the approach of Laß et al. (2023) and Botha et al. (2023), we calculated the daily commuting time by dividing the weekly commuting time by the usual number of working days per week in the main job (resulting in the average commuting time per working day). As we have no

information in the data on the number of WFH days or office days (i.e. the frequency of commuting), we cannot determine the daily commuting time per office day. Overall, the results were very similar to those from the models using the weekly commuting time as dependent variable.

5. Discussion and conclusion

This paper complements previous literature on the association between WFH and commuting behaviour in several ways. First, we deployed 18 waves of panel data from the HILDA Survey and applied fixed effects (FE) panel regression models to examine how changes in WFH are associated with changes in commuting time. These models brought us closer to identifying the causal effect by implicitly controlling for all time-constant unobserved characteristics. The comparison with pooled OLS models suggested that cross-sectional models substantially underestimate the reductions in commuting associated with low and medium shares of WFH and slightly overestimate the reductions associated with high shares of WFH. Second, we measured WFH using both a dichotomous indicator as well as the share of time worked from home per week, thereby taking into account possible effect heterogeneity in terms of the extent of WFH. Commuting was measured using weekly commuting time, which has been described as preferable to one-way commutes in the literature. Third, we examined the potential moderating role of gender. Fourth, we estimated impact function FE models that allow to investigate how the effect of WFH on commuting time evolves over the course of the home working episode.

The results of the extended FE models showed that doing any work from home was associated with a significant decrease in weekly commuting time of 14 %, supporting hypothesis *H1a*. This finding is consistent with the notion of a substitution effect and supports the literature which concludes that WFH leads to a decrease in overall commuting (e.g. Andreev et al., 2010; Lachapelle et al., 2018; Eldér, 2020). It also provides an insightful contrast to the panel study by de Vos et al. (2018), who used daily instead of weekly commuting time (measured as the time it takes to travel from home to work) and found that teleworking was associated with 5 % longer daily commuting times. However, as the weekly commuting time indicator takes into account commuting frequency as well as daily commuting time, we argue that it constitutes a more accurate measure of the overall changes in commuting.

Additionally, considering the extent of WFH revealed that low shares of WFH were associated with similar commutes compared to workers who do not work from home at all, whereas higher shares were associated with shorter commutes. Overall, the reduction in commuting time was much larger in the top category than in the other categories, supporting hypothesis *H2a* as well as existing findings (e.g. de Abreu e Silva and Melo, 2018b; Eldér, 2020). A large share of time worked from home likely represents several entire working days spent at home rather than in the office. By contrast, smaller shares of time worked from home may for many workers simply reflect work brought home in addition to a full day in the office.

Our study also highlights important gender differences in the effect of WFH on commuting. Overall, we found larger reductions in commuting time among female home workers, supporting hypothesis *H1b*. This is in line with our expectation that, due to traditional gender roles, commuting is associated with higher costs for women, and the time-saving potential of WFH is therefore more important for them. Focusing on the extent of home working, the gender-differentiated analysis revealed that the effects of a share of WFH between 20–39 %, 40–59 % and 80–100 % differed significantly between the genders, with reductions in commuting time again significantly larger for women. In fact, for men, we observed that commuting times were slightly longer among those WFH 20–39 % of their time compared to those not WFH at all. As further analyses showed, this positive association was driven by a few select industries that may potentially be characterised by a high share of employees with intensive work-related travel (e.g. business

trips, on-site customer service). Overall, however, these results confirm hypothesis *H2b* as well as findings from the literature (e.g. Sullivan and Lewis, 2001; Powel and Craig, 2015) suggesting that men are more likely to use WFH to perform additional work, e.g. in the evenings or on weekends, rather than to replace regular office hours with WFH. One could also speculate about a possible selection effect in that a temporarily high career orientation leads men to commute long hours and to additionally work at home in the evenings.

The results of FE models with impact functions (analysing commuting trajectories over time) revealed that the reduction in commuting time occurred immediately with the start of WFH. Moreover, the time savings tended to increase over time (supporting *H3*). The latter finding suggests little or no counteracting effects from potential changes in residence and work location, and is in line with existing empirical studies, which were, however, based on cross-sectional, retrospective or intentional data (e.g. Muhammed et al., 2007; Ettema, 2010; Kim, 2016). Further analyses suggested that the observed commuting trajectory was due to employees being able to expand their share of WFH over time. This may be due to workers optimizing their work environment at home, becoming more competent in managing their work at home, or employers becoming more trusting in workers performing work at home and thus allowing them to spend a greater share of their working time at home.

In terms of policy implications, to provide some – tentative – insights into how much commuting time may be saved in the future through WFH, we combined our estimates with the findings from recent surveys among Australian workers on their stated preferences regarding the share of WFH (Mattey et al., 2020; Beck and Hensher, 2021; Petrie, 2022). If future home workers behaved similarly to the home workers that our FE regression analysis was based on, and the preferences expressed in the surveys were fully accommodated, we would find an overall decline in commuting times compared to 2019 of 17 % to 25 %. However, it should be noted that using workers' stated preferences means that the scenarios presented likely show the maximum potential savings in weekly commuting time, since the realisation of these preferences depends on many factors (e.g. Mokhtarian and Salomon, 1994). Preferences may also change over time (Kogus et al., 2023), although a recent study for Australia showed relatively stable preferences for WFH between the COVID and the post-COVID period (Petrie, 2023). Moreover, the extent to which WFH actually reduces daily traffic also depends on its effects on non-work-related trips (e.g., to go shopping) as well as on the mobility behaviour of other household members (e.g. Allen et al., 2015; Kim, 2016; Caldarella and Sorrell, 2022).

We acknowledge that our study has limitations. First, our study could not account for the possibility that workers may also change their mode of transport when starting to work from home. The literature suggests that car use and the use of active transportation modes increase with WFH (de Abreu e Silva and Melo, 2018a; Eldér, 2020). Assuming that the use of a car increases commuting speed, our results might be overestimated, while in case of an increased use of active modes our results might be underestimated. Second, since our data did not contain information about commuting frequency, it was not possible to determine the extent to which commute trips are actually saved through WFH or the extent to which WFH is an incentive for longer daily commutes, i.e. the extent to which commuting time per office day (or distance between home and work) may increase when people start WFH. Future research could quantify the relevance of this mechanism for Australia. Third, although we used panel data and FE models, no conclusive statements on causality were possible. Nevertheless, our results have demonstrated the usefulness of such a methodological approach, and we therefore recommend it for future research. Fourth, it is up to future research to confirm that our findings based on the pre-pandemic period hold true in a post-pandemic world, in which WFH has become accessible to a much larger proportion of the workforce. However, we gain some confidence in the future relevance of our findings from the fact that persons who started or extended WFH during the pandemic resemble those who were

already WFH in terms of socio-demographic characteristics (Reiffer et al., 2022; Salon et al., 2022; Richards et al., 2024) and key motivations for WFH (Thompson et al., 2022). Moreover, Faber et al. (2023) in their panel study using Dutch data from before and during COVID-19 found that the negative effect of WFH on commuting time was stable over time when looking at the unstandardised coefficients. However, the standardised effect was more negative during the pandemic than before the pandemic, which the authors attributed to changes in the variances of WFH and commute time. Furthermore, it can be argued that the predictive power of COVID data for the future relationship between WFH and commuting time may also be subject to limitations, as the pandemic was an exceptional period characterised by severe travel restrictions, e.g. due to lockdowns and office closures (e.g. Jain et al., 2022).

Overall, our findings suggest that WFH has the potential for significant savings on commuting time, supporting the hopes expressed by scholars that WFH can reduce congestion, pollution, and energy consumption (e.g. Nilles et al., 1976; Harkness, 1977). Yet these savings are largely contingent on the future share of workers using WFH extensively, which was the case for only a minority before the pandemic. More extensive shares of WFH have also been shown to be beneficial for family life by reducing work-family conflict (Gajendran and Harrison, 2007; Laß and Wooden, 2023). By contrast, with respect to organizational outcomes, moderate rather than extensive WFH shares appear to be most beneficial (Allen et al., 2015). Moreover, high shares of WFH have been associated with more health complaints (e.g. Wöhrmann and Ebner, 2021). These mixed findings call for further research on all relevant outcomes at the individual, organisational, economic, environmental, and societal level to identify the optimal extent of WFH.

Appendix

Table A1

Distribution of characteristics in the sample (in % unless stated otherwise).

	All	Men	Women	Works from home	On-site only
Weekly commuting time (mean hrs)	4.42	4.87	3.98	4.92	4.31
Share of time worked from home (%)					
None	82.22	82.70	81.76	0.00	100.00
1–19	11.42	12.15	10.70	64.25	0.00
20–39	4.30	3.54	5.04	24.19	0.00
40–59	0.98	0.78	1.18	5.53	0.00
60–79	0.34	0.32	0.36	1.91	0.00
80–100	0.73	0.50	0.96	4.12	0.00
Years in paid work (mean)	18.46	19.56	17.38	21.44	17.81
Partner in household	66.56	68.88	64.28	78.48	63.97
Partner's weekly wage (mean in 100A\$)	5.68	4.26	7.09	7.43	5.30
Children in household	44.53	44.23	44.81	55.86	42.07
Educational level					
Postgraduate	6.08	5.98	6.18	14.08	4.34
Graduate diploma/certificate	7.17	5.68	8.63	15.39	5.38
Bachelor or honours	18.22	15.79	20.60	28.91	15.90
Advanced diploma, diploma	9.95	8.96	10.92	12.49	9.40
Certificate III or IV	22.90	28.38	17.53	13.00	25.05
Year 12	17.50	17.34	17.65	9.47	19.24
Year 11 and below	18.19	17.88	18.49	6.66	20.69
Remoteness area					
Major cities	70.02	69.98	70.05	75.42	68.85
Inner regional	19.85	19.82	19.89	16.65	20.55
Outer regional, (very) remote	10.13	10.20	10.06	7.93	10.61
Working hours/week (mean)	37.01	41.38	32.71	42.08	35.91
Working days/week (mean)	4.68	4.92	4.44	4.85	4.64
Occupation					
Managers	11.54	14.41	8.72	23.51	8.95
Professionals	25.55	21.27	29.75	51.58	19.90
Technicians and trades workers	12.52	21.16	4.02	4.77	14.20
Community and personal service workers	11.67	7.22	16.03	4.88	13.14
Clerical and administrative service workers	15.92	8.31	23.39	9.15	17.38

(continued on next page)

CRediT authorship contribution statement

Heiko Rüger: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Inga Laß:** Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Nico Stawarz:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Alexandra Mergener:** Conceptualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table A1 (continued)

	All	Men	Women	Works from home	On-site only
Sales workers	8.73	6.02	11.39	4.33	9.68
Machinery operators and drivers	6.08	11.20	1.05	0.77	7.24
Labourers	8.00	10.40	5.64	1.01	9.51
Industry					
Agriculture, forestry, fishing	1.30	1.96	0.66	0.89	1.39
Mining	2.01	3.43	0.60	1.48	2.12
Manufacturing	9.06	13.89	4.31	5.92	9.74
Electricity, gas, water, waste services	1.20	1.89	0.51	0.83	1.28
Construction	6.03	10.82	1.34	3.43	6.60
Wholesale trade	3.31	4.50	2.14	4.24	3.11
Retail trade	9.85	8.12	11.56	3.43	11.24
Accommodation, food services	5.75	4.67	6.81	1.49	6.67
Transport, postal, warehousing	4.37	6.79	2.00	2.30	4.82
Information media, telecommunications	2.16	2.31	2.02	3.13	1.95
Financial and insurance services	4.03	3.56	4.50	5.46	3.73
Rental, hiring, real estate services	1.34	1.12	1.56	2.10	1.17
Professional, scientific, technical services	6.86	7.21	6.52	11.15	5.93
Administrative and support services	2.45	2.11	2.78	1.75	2.60
Public administration and safety	8.39	9.86	6.95	6.66	8.77
Education and training	11.53	6.39	16.58	32.84	6.91
Health care and social assistance	15.53	5.70	25.20	9.11	16.93
Arts and recreation services	1.65	1.87	1.44	1.37	1.71
Other services	3.16	3.81	2.53	2.45	3.32
Firm size					
Less than 20 employees	18.47	19.56	17.41	13.80	19.49
20–99 employees	14.72	15.47	13.99	13.81	14.92
100–499 employees	12.76	13.61	11.92	14.08	12.47
500 + employees	48.73	47.16	50.26	55.44	47.27
Unknown/implausible	5.32	4.19	6.43	2.87	5.85
Daily wage (mean in 10 A\$)	21.45	24.57	18.38	28.27	19.97
Multiple job holder	8.06	6.77	9.32	7.95	8.08
n(observations)	112,197	55,603	56,594	19,995	92,202

Table A2

Distribution of characteristics in the sample (only workers who change working from home category; in % unless stated otherwise).

	On-site only	Works from home		
		1–19 %	20–59 %	60–100 %
Weekly commuting time (mean hrs)	4.72	5.11	5.13	2.52
Years in paid work (mean)	19.17	21.27	21.92	20.94
Partner in household	71.95	78.25	78.75	79.60
Partner's weekly wage (mean in 100A\$)	6.63	7.17	7.90	8.07
Children in household	48.92	54.60	60.51	56.02
Educational level				
Postgraduate	8.16	12.62	18.05	13.76
Graduate diploma/certificate	9.56	14.43	18.96	10.68
Bachelor or honours	23.62	28.35	31.64	18.86
Advanced diploma, diploma	12.23	12.83	11.40	15.21
Certificate III or IV	20.03	14.73	8.85	15.11
Year 12	15.52	9.84	7.65	14.24
Year 11 and below	10.88	7.20	3.45	12.13
Remoteness area				
Major cities	72.90	75.93	75.23	73.53
Inner regional	18.16	16.14	17.78	17.61
Outer regional, (very) remote	8.94	7.93	6.98	8.85
Working hours/week (mean)	37.76	43.29	41.26	32.24
Working days/week	4.70	4.90	4.76	4.70
Occupation				
Managers	16.06	26.01	19.23	15.30
Professionals	32.18	47.19	64.50	42.25
Technicians and trades workers	10.15	5.82	2.32	4.52
Community and personal service workers	11.02	5.43	3.17	7.31
Clerical and administrative service workers	16.95	8.71	6.86	24.64
Sales workers	6.86	4.92	3.06	2.79
Machinery operators and drivers	3.10	0.94	0.33	0.38
Labourers	3.66	0.98	0.53	2.79
Industry				
Agriculture, forestry, fishing	1.06	0.68	0.53	4.04
Mining	1.80	1.91	0.84	0.48
Manufacturing	7.01	6.76	3.91	5.29
Electricity, gas, water, waste services	1.16	1.02	0.56	0.48
Construction	4.63	4.03	1.57	4.43
Wholesale trade	3.14	4.57	3.57	4.04

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Table A2 (continued)

	On-site only	Works from home 1–19 %	20–59 %	60–100 %
Retail trade	7.92	4.22	1.78	2.31
Accommodation, food services	4.25	1.75	0.72	1.73
Transport, postal, warehousing	4.09	2.63	1.51	2.98
Information media, telecommunications	2.95	3.06	3.25	3.37
Financial and insurance services	5.39	5.18	6.46	6.35
Rental, hiring, real estate services	1.51	1.92	1.97	2.98
Professional, scientific, technical services	9.43	10.52	10.40	19.44
Administrative and support services	2.44	1.48	1.39	6.26
Public administration and safety	10.96	8.20	4.26	3.46
Education and training	11.69	27.92	47.25	17.81
Health care and social assistance	16.29	10.39	6.72	7.99
Arts and recreation services	1.79	1.55	0.95	1.06
Other services	2.49	2.22	2.37	5.49
Firm size				
Less than 20 employees	15.52	11.88	10.92	37.44
20–99 employees	15.28	14.40	11.98	14.63
100–499 employees	14.20	15.14	13.05	11.26
500 + employees	51.16	56.02	60.69	34.26
Unknown/implausible	3.84	2.56	3.36	2.41
Daily wage (mean in 10 A\$)	24.14	29.13	28.14	21.19
Multiple job holder	8.99	6.84	8.23	18.38
n(observations)	28,591	11,980	5685	1039

Table A3

Doing any work from home and (ln) weekly commuting time: Results from fixed-effects regression (b-coefficients).

	All base model	All extended model	Men base model	Men extended model	Women base model	Women extended model
Works from home (ref. = no)	−0.092**	−0.149**	−0.022	−0.063**	−0.158**	−0.229**
Survey year (ref. = 2002)						
2003	0.022	0.010	0.044*	0.079**	−0.001	−0.028
2004	0.055**	0.032	0.066**	0.134**	0.044	−0.004
2005	0.086**	0.055+	0.073**	0.178**	0.098**	0.031
2006	0.109**	0.061	0.098**	0.237**	0.119**	0.017
2007	0.144**	0.086+	0.151**	0.316**	0.135**	0.023
2008	0.140**	0.068	0.172**	0.364**	0.106**	−0.025
2009	0.169**	0.087	0.183**	0.416**	0.151**	−0.005
2010	0.178**	0.085	0.217**	0.481**	0.137**	−0.038
2011	0.205**	0.096	0.225**	0.515**	0.182**	−0.014
2012	0.232**	0.110	0.264**	0.588**	0.199**	−0.026
2013	0.228**	0.098	0.250**	0.613**	0.204**	−0.044
2014	0.254**	0.114	0.279**	0.673**	0.226**	−0.035
2015	0.283**	0.127	0.291**	0.715**	0.272**	−0.016
2016	0.329**	0.159	0.355**	0.811**	0.301**	−0.014
2017	0.349**	0.162	0.371**	0.857**	0.326**	−0.022
2018	0.368**	0.161	0.407**	0.918**	0.329**	−0.047
2019	0.386**	0.151	0.383**	0.918**	0.387**	−0.033
Years in paid work		0.010		−0.030*		0.015
Years in paid work squared		−0.000*		−0.000**		−0.000
Partner in household		0.070**		0.068**		0.045+
Partner's weekly wage (in 100A\$)		−0.002+		0.001		−0.001
Children in household		−0.008		0.047*		−0.042+
Educational level (ref. = Postgraduate)						
Graduate diploma/certificate		−0.011		−0.112		0.056
Bachelor or honours		0.047		−0.023		0.091
Advanced diploma, diploma		−0.052		−0.122		−0.000
Certificate III or IV		−0.159**		−0.243**		−0.107
Year 12		−0.112*		−0.141*		−0.092
Year 11 and below		−0.332**		−0.391**		−0.286**
Remoteness area (ref. = major cities)						
Inner regional		−0.279**		−0.214**		−0.345**
Outer regional, (very) remote		−0.499**		−0.522**		−0.473**
Working hours/week		0.010**		0.005**		0.014**
Working days/week		0.069**		0.055**		0.066**
Occupation (ref. = managers)						
Professionals		0.049**		0.051*		0.043
Technicians and trades workers		0.011		0.025		−0.026
Community and personal service workers		−0.032		−0.051		−0.028
Clerical and administrative service workers		0.025		0.054*		0.010
Sales workers		−0.081**		−0.087**		−0.072*
Machinery operators and drivers		−0.056+		−0.055		−0.049
Labourers		−0.059*		−0.066*		−0.052

(continued on next page)

Table A3 (continued)

	All base model	All extended model	Men base model	Men extended model	Women base model	Women extended model
Industry (ref. = agriculture, forestry, fishing)						
Mining		0.087		0.119		0.015
Manufacturing		−0.029		−0.034		−0.044
Electricity, gas, water, waste services		0.119		0.046		0.272
Construction		0.117 ⁺		0.131 ⁺		−0.016
Wholesale trade		0.011		−0.006		0.015
Retail trade		−0.150 [*]		−0.163 [*]		−0.152
Accommodation, food services		−0.210 ^{**}		−0.305 ^{**}		−0.161
Transport, postal, warehousing		−0.023		−0.024		−0.065
Information media, telecommunications		0.073		0.074		0.047
Financial and insurance services		0.158 [*]		0.119		0.163
Rental, hiring, real estate services		0.017		−0.022		0.044
Professional, scientific, technical services		0.115 ⁺		0.080		0.137
Administrative and support services		0.085		0.079		0.077
Public administration and safety		0.104		0.089		0.104
Education and training		0.037		−0.080		0.107
Health care and social assistance		0.040		−0.079		0.089
Arts and recreation services		0.025		−0.012		0.042
Other services		0.013		0.003		0.017
Firm size (ref. = less than 20 employees)						
20–99 employees		0.079 ^{**}		0.067 ^{**}		0.090 ^{**}
100–499 employees		0.151 ^{**}		0.137 ^{**}		0.167 ^{**}
500 + employees		0.154 ^{**}		0.139 ^{**}		0.169 ^{**}
Unknown/implausible		0.136 ^{**}		0.101 ^{**}		0.163 ^{**}
Daily wage (in 10 A\$)		0.004 ^{**}		0.003 ^{**}		0.005 ^{**}
Multiple job holder		0.212 ^{**}		0.135 ^{**}		0.267 ^{**}
Constant	0.820 ^{**}	0.084	0.928 ^{**}	0.903 ^{**}	0.716 ^{**}	−0.151
n(observations)	112,197	112,197	55,603	55,603	56,594	56,594
adj. within-R ²	0.012	0.060	0.014	0.053	0.011	0.073

Note: **, * and ⁺ denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Table A4

Time worked from home and (ln) weekly commuting time: Results from fixed-effects and pooled OLS regression (b-coefficients).

	All extended model	Men extended model	Women extended model
Excluding multiple job holders (FE regression)			
Share of time worked from home (% , ref. = none)			
1–19	0.004	0.015	−0.007
20–39	0.014	0.052 [*]	−0.011
40–59	−0.064 ⁺	0.037	−0.119 ^{**}
60–79	−0.430 ^{**}	−0.440 ^{**}	−0.358 ^{**}
80–100	−4.250 ^{**}	−3.535 ^{**}	−4.647 ^{**}
n(observations)	103,103	51,819	51,284
adj. within-R ²	0.152	0.106	0.197
Excluding specific industries (FE regression)			
Share of time worked from home (% , ref. = none)			
1–19	−0.003	−0.000	−0.007
20–39	−0.004	0.016	−0.014
40–59	−0.067 ⁺	0.006	−0.106 [*]
60–79	−0.397 ^{**}	−0.424 ^{**}	−0.342 ^{**}
80–100	−3.765 ^{**}	−3.390 ^{**}	−3.954 ^{**}
n(observations)	95,626	47,962	47,664
adj. within-R ²	0.140	0.098	0.179
Changes within same job (FE regression)			
Share of time worked from home (% , ref. = none)			
1–19	−0.009	−0.004	−0.013
20–39	−0.016	0.013	−0.035
40–59	−0.109 ^{**}	−0.044	−0.150 ^{**}
60–79	−0.391 ^{**}	−0.405 ^{**}	−0.355 ^{**}
80–100	−3.389 ^{**}	−2.931 ^{**}	−3.647 ^{**}
n(observations)	112,134	55,580	56,554
adj. within-R ²	0.104	0.066	0.140
Pooled OLS regression			
Share of time worked from home (% , ref. = none)			
1–19	0.008	0.021	0.000
20–39	0.047 [*]	0.089 ^{**}	0.026
40–59	0.034	0.094 ⁺	0.010
60–79	−0.189 ^{**}	−0.214 [*]	−0.168 [*]
80–100	−4.376 ^{**}	−3.782 ^{**}	−4.644 ^{**}
n(observations)	47,276	22,755	24,521
adj. R ²	0.303	0.238	0.335
Hours worked from home (FE regression)			
Number of hours usually worked from home per week (ref. = none)			

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Table A4 (continued)

	All extended model	Men extended model	Women extended model
1–7	−0.020 ⁺	0.005	−0.041 [*]
8–15	−0.163 ^{**}	−0.007	−0.299 ^{**}
16–23	−0.490 ^{**}	−0.139 [*]	−0.773 ^{**}
24–31	−1.167 ^{**}	−0.456 ^{**}	−1.772 ^{**}
32–39	−3.153 ^{**}	−2.190 ^{**}	−4.070 ^{**}
≥40	−3.532 ^{**}	−2.970 ^{**}	−4.207 ^{**}
n(observations)	112,134	55,580	56,554
adj. within-R ²	0.103	0.085	0.131

Notes: **, * and ⁺ denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively. Control variables as in the extended models in Table A3, pooled OLS models additional account for country of birth/origin.

Table A5

Time worked from home and (ln) daily commuting time: Results from fixed-effects regression (b-coefficients).

	All extended model	Men extended model	Women extended model
Share of time worked from home (%; ref. = none)			
1–19	0.013	0.023	0.001
20–39	0.029	0.060 [*]	0.010
40–59	−0.061 ⁺	0.044	−0.125 ^{**}
60–79	−0.404 ^{**}	−0.357 ^{**}	−0.411 ^{**}
80–100	−3.924 ^{**}	−3.377 ^{**}	−4.202 ^{**}
n(observations)	112,134	55,580	56,554
adj. within-R ²	0.129	0.093	0.162

Notes: **, * and ⁺ denote statistical significance at the 0.01, 0.05 and 0.10 levels, respectively. Control variables as in the extended models in Table A3, but with the number of working days per week omitted.

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