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Household commuting time and job changes

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ABSTRACT

Commuting, job change, and residential relocation significantly impact workers' quality of life, labor market dynamics, and urban planning. Furthermore, commuting also relates to life events within the household, especially those related to spatial choices, but existing research often overlooks the intricacies of the dynamic behaviors and responses to these events. This study explores how job changes and residential relocations impact commuting times within married couples, contributing to the literature on commuting, job mobility, and household decision-making dynamics. Using data from the Panel Study of Income Dynamics (2011–2019), we examine patterns in commuting times following job transitions. Our findings reveal that when husbands change jobs, their commuting time generally decreases, while wives' commuting times remain largely unaffected. Conversely, wives experience an increase in commuting time upon changing jobs, only if the job change leads to a higher wage. In cases where both spouses change jobs simultaneously, the husband's commuting time rises significantly, whereas the wife's commuting time shows no change. This research provides new insights into the joint decision-making processes within households, emphasizing the interplay between job changes and commuting behavior at the household level. These findings hold implications for policies aimed at supporting equitable access to well-connected job opportunities, particularly to accommodate longer commutes associated with specific job changes, while considering the distinct commuting patterns of dual-earner households.

1. Introduction

This paper investigates the commutes of individuals in couples, exploring the interplay between the commuting times of both partners. The primary emphasis is on understanding how commuting time is influenced by changes in one's job and the job changes of the spouse, as well as by residential relocation, from a household-level perspective. The study utilizes panel data from the Panel Study of Income Dynamics (PSID), a household survey spanning the years 2011–2019. Commuting to/from work is one of the most important trips in the everyday mobility of workers, and trends suggest that commuting times and distances are increasing in many developed countries (Kirby and LeSage, 2009; Gimenez-Nadal et al., 2022). For instance, in the US the average worker spends about 50 min per day commuting (Gimenez-Nadal et al., 2021).[1]

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[1] These figures have been changed somewhat by the increase in working from home practices (Barrero et al., 2023).

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The analysis of commuting behavior is important, as long commutes have many negative consequences for workers, firms, and society, which may vary by types of households and workers. Longer commutes are associated with decreased subjective health (Kunn-Nelen, 2016), lower psychological wellbeing (Roberts et al., 2011; Dickerson et al., 2014), and low levels of "instant enjoyment" (Kahneman and Krueger, 2006). Other authors have found that longer commutes are related to high levels of stress (Gottholmseder et al., 2009; Wener et al., 2003; Frey and Stutzer, 2008), and to increased sickness absenteeism (Van Ommeren and Gutiérrez-i-Puigarnau, 2011). For firms, longer commutes are related to decreased worker productivity (Grinza and Rycx, 2020) and increased shirking behaviors (Ross and Zenou, 2008), and firms are often expected to compensate workers with wage premia for their long commutes (Leigh, 1986; Ross and Zenou, 2008; Ruppert et al., 2009; Mulalic et al., 2014). Furthermore, modes of commuting have significant environmental and social impacts. For instance, commutes by motorized travel modes are closely tied to emissions and congestion during peak hours, which contribute to air pollution and reduced quality of life in urban areas (Coria and Zhang, 2015, 2017; Long and Szeto, 2019; Vosough et al., 2020). These effects underscore the need for sustainable transportation policies that can help mitigate these negative outcomes.

Despite these costs of long commuting, there are also benefits to commuting. For example, commuting provides workers with a transition period between work and their personal lives, as recent research has concluded that work from home blurs the barriers between work and non-work activities, ultimately affecting workers' wellbeing (Fujiwara et al., 2020; Ruiz et al., 2021). Commuting is also linked to higher wages, as firms often pay compensating wages in exchange for long commutes (e.g., Ross and Zenou, 2008; Fu and Ross, 2013), and to higher rates of homeownership (Morris and Zhou, 2018). Furthermore, for firms, commuting allows them to attract employees from wide geographical areas, and long commutes relate to career promotion (Sandow and Westin, 2010), increasing the access to skills and expertise, which could ultimately benefit the firm's performance.

Although commuting has been studied by several authors, with some degree of consensus regarding certain factors affecting or being affected by commuting, it is a complex phenomenon in which many elements come into play and, as such, remains relatively unexplored (van Ommeren and van der Straaten, 2008). One factor that has often been related to commuting behaviors is family, and several authors have documented a gender gap in commuting time and commuting distance.[2] Commuting also relates to household composition (McQuaid and Chen, 2012; Neto et al., 2015), and commuting time is considered a shock to worker time allocations (Ross and Zenou, 2008).

Despite extensive recognition in the scholarly literature of the importance of intra-household factors, many studies have predominantly relied on cross-sectional data, overlooking the complexities of dynamic commuting behaviors within household contexts. On one hand, commuting is determined by lifecourse events related to spatial choices such as residential relocation, but also to others such as changes in family composition or retirement, which inevitably shape travel behavior in general terms (Beige and Axhausen, 2017). On the other hand, long commutes can create strains by reducing the time available for family responsibilities, household labor, and caregiving (Giménez-Nadal and Molina, 2016). This time limitation often requires other household members to adjust their schedules and workloads, potentially leading to imbalances or increased stress, especially if caregiving responsibilities are unequally distributed (e.g., Aguiar and Hurst, 2007). Additionally, the psychological toll of long commutes, such as stress or fatigue (Frey and Stutzer, 2008), can also affect household interactions and the emotional environment at home, impacting the wellbeing of all members.

Despite this, the empirical literature often overlooks the intricacies of the dynamic behaviors and responses to these events, due to the scarcity of detailed longitudinal household data. The analysis of commuting as an evolving process within households has been limited, largely due to a scarcity of longitudinal data that can capture changes over time. This gap has led to an emphasis on individualistic or static characterizations of commuting, as noted by Gimenez-Nadal et al. (2021). However, studying commuting at the household level is critical, given that spousal workplace locations and household decisions significantly shape individual commuting behaviors and responses to job changes (Beige and Axhausen, 2017; Ma et al., 2025).

Within this framework, our primary objective relates to the limited literature examining the relationship between changes in job situations, residential relocation, and commuting times from a household perspective and using longitudinal data, analyzing both husbands and wives in two-member households. In doing so, we also compare how the commuting time responses to job changes may differ between husbands and wives, which is our secondary objective. We utilize panel data from the PSID covering the period from 2011 to 2019. To disentangle the potential influence of residential relocations, often concurrent with job changes, we net out residential moving when it occurs near in time to job changes, and we analyze residential moving and job changes when they occur simultaneously in the mid-run. Additionally, we control for demographics and household characteristics, isolating both observable and unobservable sources of heterogeneity.

We contribute to the empirical analysis of commuting times within the context of households, with a primary focus on changes in the commuting times of both husbands and wives driven by spouses' job changes, and by household residential relocation. Although the relationships between worker commuting behavior, job change, and residential relocation have already been analyzed, to the best of our knowledge, this is the first analysis of commuting time and residential/job relocation at the household level and using longitudinal data that allows to study changes in commute duration and to account for unobserved factors. The combination of this household-level approach with a panel database enriches our understanding of the dynamics of husband and wife commuting behaviors (particularly commuting times) and their interplay, an aspect that has been considered important but has received limited attention compared to studies of individual worker commuting time based on static cross-sectional data.

[2] See, for instance, White (1986), Scheiner (2010), Roberts et al. (2011), McQuaid and Chen (2012), Albert et al. (2019), Le Barbanchon et al. (2021), and Gimenez-Nadal et al. (2022).

The rest of the paper is structured as follows. Section 2 reviews existing research on commuting and residence and job change, and Section 3 shows the conceptual framework. Section 4 describes the data and variables. Sections 5 and 6 show the empirical strategy and the results, respectively. Finally, Section 7 discusses our results, and Section 8 concludes.

2. Literature review

Commuting is a phenomenon related to other worker time allocations (Iwata and Tamada, 2014; Gimenez-Nadal et al., 2018b), subjective wellbeing (Dickerson et al., 2014), employment characteristics (van Ommeren and van der Straaten, 2008; Gimenez-Nadal et al., 2018a; Albert et al., 2019), gender roles (Sandow and Westin, 2010; Oreffice and Sansone, 2023), urban forms (Manning, 2003; Gobillon et al., 2007; van Acker and Witlox, 2011), and the business cycle (Kim and Horner, 2021), among others.[3] In the next subsections, we review the relevant literature on the determinants of commuting, i.e., general factors that relate to commuting behavior and more specifically commuting time; on life course events that relate to changes in commuting time, with a focus on job and residential relocation; and on household level studies on commuting time.

2.1. Determinants of commuting time

Commuting behavior in general terms, and commuting time in particular, is related to several socio-demographic and economic worker attributes, such as gender, education, wages, and other time allocation. For instance, the literature has concluded that males usually spend more time commuting to/from work than females, even when controlling for several observable characteristics, which may reflect preferences as well as time constraints from household and caregiving responsibilities discussed below; see Gimenez-Nadal et al. (2022) for a recent review. Other authors have concluded that highly educated workers may look for specific jobs that are far from their workplaces, which typically involve a longer commute distance (e.g., Ross and Zenou, 2008; Dargay & Clark, 2012), as well as longer commuting time (Gimenez-Nadal et al., 2018b), as specialization and skill matching enlarges the relevant job-search radius, raising expected commuting distance and time.[4] Relatedly, many studies have found a positive relationship between wages and commuting (see Gimenez-Nadal et al. (2018b) and Wong et al. (2020) for recent studies in the US), and some models assume that commuting time is a shock to workers' time allocation, which ultimately reduces the time available for other activities (Ross and Zenou, 2008), in line with the results in the US by Gimenez-Nadal et al. (2018b). This is consistent with compensating differentials, whereby higher pay offsets the time cost of longer commutes.

Other household characteristics that relate to commuting time include available transportation modes or family composition. For instance, the presence of children often reduces commuting time for women due to caregiving responsibilities (Lee and McDonald, 2018) and can moderate the impact of commuting time on work hours (Carta and De Philippis, 2018). This reflects the need for mothers to remain closer to home, adjusting labor supply and commuting choices to accommodate childcare due to time constraints. Additionally, married workers tend to have shorter commutes compared to single workers (Roberts et al., 2011), as marriage may increase the value of time spent at home, encouraging residential or job choices that limit commuting. See McQuaid and Chen (2012) for an exploration of commuting times and worker socio-demographic/economic attributes.

Commuting is also closely linked to the built environment. In traditional urban models, such as the monocentric (Alonso, 1964; Mills, 1967; Muth, 1969) or polycentric (Knox and McCarthy, 2005) models, commuting distance is determined by the trade-off between the cost of commuting, which rises with distance from the business district, and the benefits of living in affordable residential areas, typically in the cities' peripheral areas in the US.[5] That trade-off shapes commuting time through its effects on distance and feasible modes. Because commuting time is a product of commuting distance, commuting modes, and other factors, commuting time is also partially determined by such a trade-off.[6] However, commuting should be considered in the context of evolving urban forms, where suburbanization, housing development, and the dynamic redistribution of employment shape commuting (see Ta et al. (2022) for a literature review). These processes change the relative location of jobs and residences, which in turn modifies commuting distances and times.

Access to transport infrastructure plays a pivotal role in shaping commuting time, influencing how far and by what means people are willing to travel for work, and accessible public transit and bike-friendly infrastructure can reduce commute times, in line with the results by Lunke et al., (2023) for Norway. Kent et al. (2019) analyze commuting time in Australia and conclude that inadequate or poorly designed transport systems can lead to car dependency, longer commuting times, and traffic congestion. The mechanism is that better transport networks expand the set of feasible jobs within an acceptable commuting threshold, while poor infrastructure imposes limits to worker choices. This is especially relevant in dense urban areas, where travel times by public transit are longer than travel times by private vehicle (Liao et al., 2020). In addition, topography, natural obstacles, and city geography play a crucial role in shaping commuting times, as Ceder et al. (2015) find that geographic features (e.g., rivers or hills) can lead to less direct routes for commuters,

[3] See recent literature reviews by Picard et al. (2018), Naess et al. (2019), and Kim and Horner (2021).

[4] Because commuting duration is affected by travel modes and other factors, time is likely to vary less across sociodemographic attributes than distance.

[5] See recent studies by Huai et al. (2021) and Liotta et al. (2022).

[6] An important aspect of commuting time is workers' personal preference for travel mode. We do not focus on preferences for travel mode, as the PSID does not have information on travel mode or preferences toward specific modes, which we acknowledge as a limitation.

compared to flat areas in which transit systems can be more easily optimized. Such physical constraints highlight that commuting patterns are not only the result of household or worker decisions but also of the spatial environment in which these decisions are made.

2.2. Life events and commuting time

Commuting behaviors relate to lifecourse events, such as decisions related to the household composition (e.g., getting married or having children). For example, Gimenez-Nadal et al. (2018a) find that those living in a couple spend more time commuting than their single counterparts in the US. This may occur because couples must coordinate two job locations and a single residence, which reduces flexibility and can increase commuting distances. McQuaid and Chen (2012) find that having kids (as well as the age of the youngest kid) relates to reduced commuting time in the UK, and similar results for Germany, the US and Korea are found in Scheiner (2016), Gimenez-Nadal et al. (2018a), and Lee and McDonald (2018), respectively. These findings suggest that the need to care for children limits the willingness of parents, especially mothers, to accept distant jobs. Despite that, Neto et al. (2015) conclude that this negative correlation is especially relevant among mothers in Brazil, and Zhao and Zhang (2018) find that having kids encourages car use for commuting purposes in China. This highlights that the mechanism linking children and commuting can differ across contexts, either reducing travel time through job choices closer to home or increasing reliance on private transport to manage family responsibilities.

Besides those kinds of life events, commuting change is crucially determined by other lifecourse events related to spatial choices, such as residential relocation or employment relocation (e.g. job changes), which inevitably shape travel behavior in general terms, and commuting in particular (Clark et al., 2003; Beige and Axhausen, 2017; Ma et al., 2025). For instance, Clark et al. (2003) conclude that households often reduce commuting distances after moving, especially when the initial separation between residence and workplace is large, while Beige and Axhausen (2017) find empirically said result in Switzerland. By contrast, job changes typically extend commuting distances, particularly when education or employment transitions occur (Beige and Axhausen, 2017; Ma et al., 2025). However, the empirical literature has predominantly focused on individual worker-level and/or cross-sectional analyses, often overlooking the intricacies of the dynamic behaviors and responses to these events, hindered by the scarcity of detailed longitudinal household data. This reliance on static approaches means that the adjustments households make over time, for example in response to simultaneous changes in jobs and residences, are not fully captured. Furthermore, to the best of our knowledge the literature has focused mostly on commuting distance and commuting modes, and not on commuting time, even though commuting time is more important from the workers' perspective as it directly reflects the actual effort and inconvenience of the commute, reflecting practical constraints on worker daily time allocation.

The intricate relationships between commuting patterns and shifts in job and residence locations are well-established across fields such as economics, geography, urban planning, and engineering. In an exploration of the interplay between commuting and job changes, van Ommeren et al. (1997, 1999) developed a search model in which employed individuals actively pursue better job and housing situations, receiving distinct offers for both employment and residence. Within this framework, individuals may be more inclined to accept longer commutes if offered compensating wages. However, given the potential for residential relocation, compensating wages do not necessarily need to fully offset commuting costs, as the prospect of changing residence offsets the increased commuting burdens. This dynamic interplay creates a complex relationship between jobs and residential changes, collectively influencing commuting distance and then also commuting time. The authors further suggest that job transitions are generally more frequent than residential relocations, largely due to the higher costs associated with the latter, particularly for homeowners, while renters exhibit higher mobility rates due to typically lower moving costs (van Ommeren et al., 1999).

The empirical findings of van Ommeren et al. (1997) for the Netherlands indicate that commuting distance negatively relates to job arrival rates, and that workers' behavior aligns with a search for better options of jobs and residences. Van Ommeren et al. (1999) find that there is not a significant relationship between residential mobility and job changes in the Netherlands, nor is there one between commuting distance on one hand, and residential mobility and job changes on the other hand. In a related study, van Ommeren et al. (1998) extend their job search model to two-earner households, demonstrating that the distance between spouses' workplaces and both spouses' commuting distances significantly impacts job change.

More recently, several authors have analyzed the relationships amongemployment, residential relocation, and commuting behavior. An important branch of the existing literature has focused on travel modes, and there is some consensus that both job transitions and residential moving shape transportation modes significantly (Schoenduwe et al., 2015), as changes in workplace or residence often require individuals to reconsider the mode of travel that best fits the new distance or location. However, the impact is heterogeneous and depends on car ownership (Haque et al., 2019), and on distances with respect to the new residence, as some relocations relate to increased use of private vehicles (e.g., those to suburban neighborhoods (Tao et al., 2023a)), while others relate to public transit. Evidence from the UK and Switzerland indicates that changes in travel mode are especially pronounced when the distance to work becomes shorter after a relocation, with individuals more likely to abandon car use in favor of public transport or active commuting options such as walking and cycling, which become more available when households adjust to new patterns of accessibility (Clark et al., 2016; Beige and Axhausen, 2017). In China, rapid urban transformations show a different mechanism, as longer commuting distances following residential relocation often push commuters toward public transit, while also sustaining private car use (Zhao and Zhang, 2018). Taken together, these findings suggest that the direction of mode shifts depends on how relocation reshapes commuting distances and the availability of transport infrastructure. Furthermore, lifecourse events with spatial implications generate some dynamics, as commute journeys play a prominent role in home relocation decisions, but after moving, commuting considerations such as those related to green-transport likely emerge again (Zarabi et al., 2019). Tao et al. (2023a) review the literature on commuting modes, life events and residential relocation. In summary, these studies show that commuting is not only a consequence of relocation decisions but also a factor shaping how households adapt after moving.

Commuting distance has also been studied. In relation to commuting distance, some authors have found a positive correlation, including results for the US (Blumenberg and King, 2019). This result suggests that moving to low density areas, typically with good amenities in US cities' peripheral areas, relates to increased commuting distance, and that households prioritize residential quality and amenities over proximity to work, which extends the daily commute. However, available transport modes and access to public transit play a pivotal role in this relationship (Prillwitz et al., 2007). Furthermore, urban forms are also crucial in this relationship between commuting distance and residential relocation, as estimates for other countries such as Canada are in line with results for the US (Akbari and Habib, 2018), while results for countries with different urban structures show opposite correlations (e.g., Beige and Axhausen, 2017; Xue et al., 2020). In relation to job change, the literature has found that, at an individual level, relocating has a small but positive effect on commuting distance in the mid run (Hrehová et al., 2023). These findings reinforce the idea that spatial context and national urban structures condition whether residential moves lengthen or shorten commutes.

Finally, some authors have also focused on job change, residential relocation, and commuting time, although from an individual rather than household perspective, assuming that the commute time of a worker is an individual isolated decision taken prioritizing own preferences over the partner's commuting condition (Ghasri and Rashidi, 2019).[7] In the US, workers tend to reduce their commuting time when facing residential changes, especially among those initially facing lengthy commutes (Clark et al., 2003), although this correlation seems not significant in other regions such as China (Ma et al., 2025). This suggests that the effectiveness of residential relocation in reducing commuting time depends on the local or national context. Besides residential relocation, some authors have concluded that job changes positively relate to commuting time in Luxembourg, China, and Germany (Sprumont et al., 2014; Yang et al., 2017; Rau et al., 2019; Ma et al., 2025). However, the same relationship has been estimated to be not significant in Canada (Gerber et al., 2020). These cross-country differences highlight again that institutional and spatial contexts mediate how job changes affect commuting time. Furthermore, job change generally induces correlations in the short run that may decrease or differ in the mid run, after workers have adapted to the new commuting journey (Von Behren et al., 2018), thus highlighting the relevance of analyzing not only the immediate change in workers' commuting after the life event, but also the impact on the mid term.

2.3. Household level studies on commuting

The literature has long recognized the importance of household level factors in determining commuting time, in addition to specific life events such as moving or having children. Despite the lack of household surveys studying commuting time, there has been a focus on empirical analyses that often control for household-related variables and therefore capture the intricacies of dynamic behaviors within the household context. Two significant dimensions of the household that relate to commuting and have received attention in recent years are the marital status and the role of the spouse in determining commuting time, as married workers often spend more time commuting than their single counterparts (Roberts et al., 2011). This reflects how partnership decisions affect residential and job choices, sometimes lengthening commutes to balance both spouses' employment opportunities, and given time constraints related to cohabitation and marriage, such as spending time together.

Some authors have focused on the US, including Christian (2012), Gimenez-Nadal et al. (2018a), and Morris and Zhou (2018), who found that commuting time relates negatively to time spent together with the spouse doing other activities, and that longer commutes relate to being married instead of being single. These results highlight the time constraints that face workers, as commuting is a shock to time allocation which ultimately limits the ability of workers to devote time to other activities such as being with the partner, while at the same time couples need to balance two workplaces and one housing. The partner's employment status, but not the partner's wage, also relates to worker's commuting time, suggesting that whether both spouses work shapes commuting choices more than relative income does.

Other authors have also examined commuting time from a household perspective in other countries, focusing on how workers' commuting relates to characteristics and behaviors of other family members. For example, longer commuting times relate to a decrease in the spouse's work hours, and to the spouse being involved in increased household responsibilities (Carta and de Philippis, 2018; Stenpaß and Kley, 2020). These findings show that one partner's long commute can indirectly reallocate labor within the household. However, some authors have found that these adjustments are more prevalent among wives than among husbands, which ultimately explains the shorter commuting times of wives (Hjorthol and Vagane, 2014). Despite that, other authors have found the opposite result (e.g., Kohara and Sekijima (2017) using Japanese data, or Kim (2020) using Korean data), highlighting the relevance of the analyzed country, the national context, and the gender norms.

[7] Maheshwari et al. (2023) provide a recent review.

The relationship between commuting and wellbeing has also been analyzed at the household level. Longer commutes often relate to adjustments by other family members that reflect the household's wellbeing (Hirte and Illmann, 2019), and household members typically consider and value the partner's commuting time (Swardh and Algers, 2016). Tus, these findings suggest that commuting costs are not borne individually but shared within the household, influencing overall welfare. Similarly, Tao et al. (2023b) find that it is husbands' wellbeing what relates to wives' commuting time, while wives' wellbeing is not related to husbands' commuting time, revealing a gender asymmetry in how commuting affects family life. In summary, the existing household-level analyses on commuting have focused on workers' marital status and the role of the spouse in determining commuting behavior, on how commuting relates to other behaviors of household members, and on household wellbeing. We contribute to the literature on commuting analyzed from a household perspective by focusing on commuting, job change, and residential relocation, using household longitudinal data from the PSID.[8] To the best of our knowledge, this represents the first analysis of these relationships at the household level.

3. Conceptual framework

Our empirical analysis draws on key theories and concepts at the intersection of urban economics, geography, and family economics. This includes human capital theory, household bargaining models, urban models, lifecycle theories, gender-based commuting studies, and research on job mobility and wage dynamics. A summary of the framework is shown in Fig. 1.

Human capital theory suggests that job changes are often motivated by the pursuit of better conditions, including higher wages, as individuals maximize utility under budget and time constraints (e.g., Chiappori et al., 2009). Commuting is seen as a cost factor, where increased wages may lead workers to accept jobs with longer commutes (Rouwendal and Rietveld, 1994; van Ommeren et al., 1997, 1999). Conversely, workers may choose jobs with shorter commutes, even at lower wages, balancing the trade-off between commuting time and leisure or family activities (Ross and Zenou, 2008; Iwata and Tamada, 2014; Gimenez-Nadal et al., 2018b). This balance also depends on household resources like vehicle availability and income, which influence commuting choices and budget constraints (McQuaid and Chen, 2012; Neto et al., 2015).

In family economics, household bargaining models highlight that spouses often have different preferences and that households do not act as single units (Chiappori, 1992). Household decisions involve trade-offs, mediated by each spouse's bargaining power. Thus, one spouse's job change affects not only their own commute but also that of their partner, reflecting the interdependence of spousal behaviors. Besides that, commuting time has been examined from the perspective of gender differences, which exist as regards commuting duration (Gimenez-Nadal et al., 2022), but also in terms of the moderating impact of gender on the relationship between commuting and wages, job types, labor market participation, or psychological wellbeing (Roberts et al., 2011; Kimbrough, 2019; Farré et al., 2023). These studies suggest that men and women face different constraints and incentives in the labor market, which makes commuting a gendered outcome. Therefore, husband (e.g., male) and wife (e.g., female) commuting times could respond differently to job changes and residential relocation, given that males and females have shown different commuting behaviors. This implies that intra-household decisions on employment and residence cannot be understood without accounting for gender-specific patterns in commuting.

Urban models also propose a trade-off between commuting and housing, where longer commutes are often weighed against the benefits of living in suburban areas with desired amenities (Brueckner et al., 1999; Prillwitz et al., 2007). Job search models further argue that commuting behaviors are shaped by the endogenous relationship between job changes and residential relocations (van Ommeren et al., 1997, 1999; Jang and Yi, 2021). Empirical evidence supports this, showing that changes in residence, education, and employment are highly interdependent and often occur simultaneously (Beige and Axhausen, 2017), and are sensitive to households' income (Jang and Yi, 2021). Household characteristics that influence preferences for mobility and shape the feasible commuting arrangements a household can sustain, such as age and household composition, as well as housing attributes like dwelling type also play roles in commuting decisions (Lee and McDonald, 2003; Roberts et al., 2011; Carta and De Philippis, 2018; Manning, 2003; Naess et al., 2019). Relatedly, lifecycle models assert that household decisions are affected by factors such as age and the presence of children. For example, younger workers and couples without children may be more willing to relocate or accept longer commutes after a job change (van Ommeren and van der Straaten, 2008; McQuaid and Chen, 2012; Gimenez-Nadal et al., 2018a), while families with children might prioritize shorter commutes and residential stability (Clark et al., 2023).

Finally, employment type and demographics also relate to commuting patterns. Self-employed workers often face distinct commuting dynamics compared to employees. The commute of self-employed individuals is influenced by their search for an available workplace, whereas employees' commuting is driven by job search. Consequently, commuting behaviors (including commuting time) of self-employed workers tend to differ from those of employees, as the former are able to optimize it further and avoid the so called "excess commuting" (van Ommeren and van der Straaten, 2008; Giménez-Nadal et al., 2018a). Besides that, workers in specialized occupations with higher education levels tend to experience longer commutes (Sandow and Westin, 2010; Dargay and Clark, 2012).

In summary, our analysis emphasizes that spousal job changes influence commuting time for both spouses due to household bargaining dynamics. Residential relocation also affects commuting and moderates the relationship between job changes and commuting time, as relocation and job changes are often interlinked. Additionally, wage impacts from job changes, along with

[8] Despite this, the PSID has previously been used to study workers' commuting behavior, but not from a household perspective (e.g., Simonsohn, 2006; Smart and Klein, 2020; Gimenez-Nadal et al., 2022b).

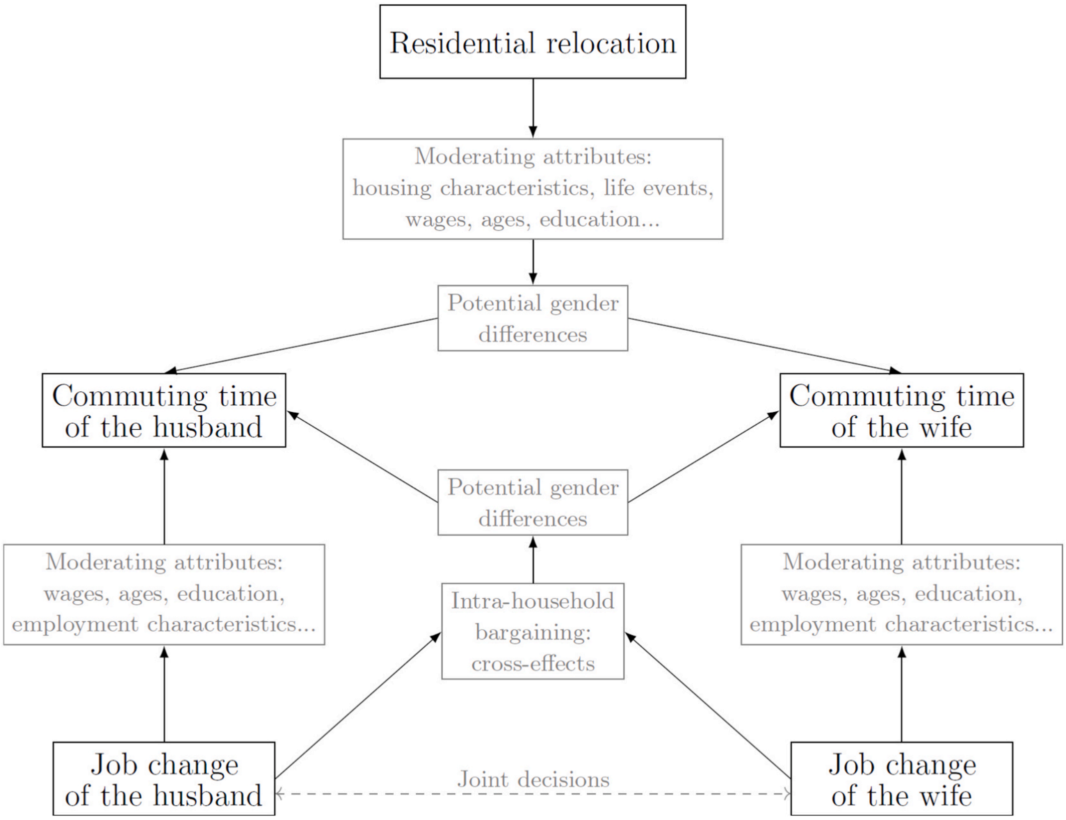

Fig. 1. Summary of the conceptual framework.

household characteristics such as the presence of children, age, and moving costs, shape preferences for residential mobility. Therefore, to comprehensively capture commuting time, we account for individual characteristics such as gender, age, education, household composition, income, and vehicle availability.

4. Data and variables

We use data sourced from the Panel Study of Income Dynamics (PSID) spanning the years 2011 to 2019, during periods of commuting availability. The PSID, administered by the University of Michigan (PSID, 2019), was established in 1968 as an extensive, nationally representative survey of US families. It covers a diverse range of data, encompassing employment and income specifics of household members, along with other relevant information. Notably, the PSID was significantly expanded in 1997, broadening its coverage to include an expanded array of topics, such as consumption patterns. Moreover, it underwent a redesign, transitioning to a biennial data collection schedule from that point onward.[9]

Of particular relevance to our study, the PSID introduced the collection of data on the commuting times of individuals within interviewed households in the year 2011. Our investigation concentrates on the survey years from 2011 to 2019, corresponding to the biennial records during which this commuting information is available. The PSID is appropriate for our analysis, as it provides information on the year individuals started working for their current employer (which allows us to study job changes), on whether households moved their residence, and on several demographic and labor market outcomes. We do not use data from the 2021 wave of the PSID, as the analysis of how COVID-19 and the subsequent widespread of work from home practices affect the relationships examined in this study is left for future research; see recent analysis on work from and commuting by Thomas et al. (2021) and Currie et al. (2021).

Since we are interested in husband and wife commuting times, we retain information on households formed by (married or unmarried) spouses, namely a husband and a wife. The offspring, parents, and other cohabitants of interviewed spouses are not

[9] We focus on the sample interviewed in the period 2011–2019, comprising the core SRC sample (originally representative), individuals from the immigrant samples added in 1997/1999 and 2017/2019, and individuals in the SEO sample. This approach ensures that the samples are adjusted to closely mirror the overall national population in the US, encompassing both non-poor and poor households, as well as immigrant households (PSID, 2021). All summary statistics and results are calculated using the designated weights provided by the PSID data.

considered for the analysis. We select working couples only (i.e., couples in which both spouses participate in the labor market), who report positive commuting time, and we require complete data on demographic and labor outcomes (e.g., earnings, hours of work, commuting, etc.).[10] Since we are interested in changes in commuting time that are driven by job changes, we retain households that, meeting the previous criteria, are followed for at least two consecutive periods. These restrictions leave a sample of 2,500 distinct households (i.e., 2,500 husbands and 2,500 wives), and the average household is observed for 3.21 periods; i.e., our sample consists of 8,013 observations (households $\times$ years).[11]

Our main variable of interest is the time spent commuting by husbands and wives in the sample, measured as the time spent in two-way commuting as follows: "On a typical day, how many minutes is your round trip commute to and from work?"[12] We thus define commuting as two-way commuting time, measured in minutes, in line with existing research that has focused on commuting time to/from work, rather than on one-way commuting (Stone and Schneider, 2016; Gimenez-Nadal et al., 2021). We also use information on job changes. We define the job change of each spouse as a dummy variable that takes value 1 if the corresponding spouse has changed his/her employer between the current survey record and the previous survey record, and 0 otherwise. To define a job change, we need details of the employer status for the current survey year and the preceding wave. Consequently, job changes are determined based on observations with data differences, over the 5,443 observations corresponding to the 2,500 households in the sample with differing information.

Because we are interested in studying the variation in commuting time driven by job changes, we could follow the identification strategy of van Ommeren and Gutiérrez-i-Puigarnau (2011), and then omit those households who moved their residence between survey records to net out a potential source of endogeneity. Existing research has shown that alterations in employment and residence typically occur concurrently rather than sequentially (Rouwendal and van der Vlist, 2005; Beige and Axhausen, 2017). However, the PSID data lacks information on whether job changes instigate residential moves or vice versa. Consequently, we cannot fully address endogeneity, leading us to retain both couples who moved (movers) and those who did not move (stayers) in the sample. Furthermore, the PSID does not include information on the built environment of residential locations, or any geographical information that allows us to locate households, only on whether households have moved between survey periods, which we acknowledge as a limitation, as we cannot control for the built environment or for location fixed effects, and we do not know if residential relocations take place from the city center to outskirts, for example. As a consequence, we can only identify whether households move, but not where and from where they move.

The PSID allows us to define several characteristics of surveyed households and individuals within those households, as well as their corresponding outcomes in the labor market, which are likely correlated to commuting and therefore need to be accounted for. We define the age of spouses, measured in years, and the squared age to capture potential non-linear effects (Gimenez-Nadal et al., 2018a). Furthermore, we categorize the highest level of education attained by spouses using four dummy variables: basic education (assigned a value of 1 for individuals without completed secondary education, 0 otherwise), secondary education (assigned a value of 1 for individuals with completed secondary but not college education, 0 otherwise), college education (assigned a value of 1 for those with a completed bachelor's degree, 0 otherwise), and higher education (assigned a value of 1 for those with completion of some postgraduate program, such as a master's degree, Ph.D., or advanced professional degree; 0 otherwise). The PSID allows us to create dummy variables identifying respondents as either white or black (with a minority of respondents corresponding to some other ethnicity).

In addition to examining individual demographic characteristics, our study incorporates various household-level demographics. This includes the number of individuals in the family unit, the count of children within the household, and the age of the youngest child, as grown children are relevant in determining commuting time. Furthermore, we include controls for housing-related variables, such as dwelling type (a binary variable with a value of 1 for house residents and 0 otherwise), the number of rooms, and tenure status (a binary variable with a value of 1 for owned homes and 0 for rented homes). Following the approach of Gimenez-Nadal et al. (2018a), we incorporate a control for household income, measured in $1,000.[13] Finally, we control for the number of vehicles, and changes in the number of vehicles, as events like car purchase or, more broadly, changes in the number of vehicles available for commuting are likely to be relevant in determining spouses' commuting times.

[10] The selection of workers with positive commuting excludes workers who work from home. However, work from home was not widespread before the COVID-19 outbreak (Barrero et al., 2023). Analyzing how the COVID-19 and the associated widespread of work from home practices have affected commuting, the proximity to workplaces, and the relationship between commuting, job change, and residential relocation is left for further research.

[11] Because the analysis and definition of certain variables requires the use of first differences, the estimation samples are smaller (5,443 observations). Since the PSID is biennial over the analyzed period, the first difference of a given variable is defined as the value of that variable in a given period, minus the value in the previous period (two calendar years in the past), in line with existing research (Blundell et al., 2016; Theloudis, 2021). A comparison of the hours of work and hourly wages within our chosen sample, juxtaposed with those in previous studies, suggests that the representativeness of our sample in terms of labor supply and wages aligns with findings in studies such as Blundell et al. (2016). Husbands in our sample earn an average wage of $36.4 per hour, while wives earn $27.1 per hour. Additionally, husbands work approximately 2,187 h per year compared to wives who work 1,809 h per year.

[12] We must acknowledge potential measurement error in the definition of commuting time, as it is based on a stylized question, and existing research has concluded that this information is more accurately measured through time-use diaries, such as those in the American Time Use Survey (Bonke, 2005; Yee-Kan, 2008). Nevertheless, time-use surveys consist of repeated cross-sections and do not include longitudinal data or information on job changes.

[13] Monetary amounts are all expressed in 2019 dollars.

Table 1
Main summary statistics.

VARIABLES	Husbands ($j = 1$)		Wives ($j = 2$)		Difference (*husband – wife*)	
	Mean	S.Dev.	Mean	S.Dev.	Diff.	*p*-value
Commuting time	46.464	39.812	39.352	31.951	7.111	(<0.001)
Changed job	0.198	0.399	0.214	0.410	−0.016	(0.039)
Changed job | Δlog(wage) > 0	0.102	0.303	0.118	0.323	−0.016	(0.008)
Changed job | Δlog(wage) < 0	0.096	0.295	0.096	0.295	0.000	(0.993)
Moved	0.220	0.414	0.220	0.414	–	–
Changed job and moved	0.061	0.240	0.066	0.248	−0.004	(0.347)
Δlog(commuting)	0.001	0.786	0.013	0.794	−0.012	(0.411)
Δlog(commuting) | job change	0.014	1.150	0.066	1.164	−0.052	(0.261)
Δlog(commuting) | job change, Δlog(wage) > 0	0.067	1.167	0.082	1.082	−0.014	(0.815)
Δlog(commuting) | job change, Δlog(wage) < 0	−0.043	1.130	0.046	1.259	−0.089	(0.205)
Δlog(commuting) | moved	0.060	0.941	0.087	1.013	−0.027	(0.493)
Δlog(commuting) | job change and moved	0.112	1.189	0.117	1.230	−0.005	(0.945)
Total observations (households X waves)			8,013			
Observations with data in difference			5,443			
Number of households			2,500			

Note: The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Statistics computed using sample weights. Total observations (households X waves) differ from observations with data in difference because differences require two consecutive waves of information. Commuting time is measured in minutes per day. Summary statistics of demographics shown in Table A1 in the Appendix A.

Table 1 shows summary statistics of the main variables of interest.[14] The average husband in our sample spends 46.5 min per day commuting to/from work, whereas the average wife spends 39.4 min per day commuting. This is a gender difference of about 7.1 min per day, which is statistically significant at standard levels. These magnitudes are in line with existing research on gender and commuting time in the US and other developed countries (e.g., Roberts et al., 2011; McQuaid and Chen, 2012; Oakil et al., 2016; Gimenez-Nadal et al., 2022). Fig. 2 shows the evolution of commuting times of husbands and wives in the sample, and displays relative stability, while the gap in commuting time between husbands and wives remains highly significant for all the years in the sample.[15] Regarding job changes, Table 1 shows that 19.8 % of the husbands in the sample report a job change since the previous survey record, as do 21.4 % of the wives.[16] The gender difference in the rate of job change is statistically significant at standard levels. As for moving, Table 1 shows that 22.0 % of the interviewed households moved residence between survey years.[17] Furthermore, 31.0 % (30.7 %) of those households in which the husband (wife) changed job, also moved.

Focusing on the change in commuting time, we define "Δlog(commuting)", for each time period and spouse, as the log of time spent commuting by a given spouse, minus the log of time spent commuting by the same spouse in the previous survey record (i.e., two calendar years in the past). That way, we measure growth rates in commuting time, and not changes measured in minutes, similarly to how the literature has addressed the dynamics of wages (e.g., Altonji et al., 2013; Blundell et al., 2016; Arellano et al., 2018). The growth rate of commuting time between consecutive records of the average husband is 0.01 %, while the corresponding rate for the average wife is 1.3 % (considering all individuals, i.e., those who moved and those who did not move, and those who changed job and those who did not). The difference between husbands and wives is found to be not significant at standard levels. Furthermore, these changes are very small, indicating that the change in commuting time between periods is about 0.05 min for the average husband, and 0.5 min for the average wife. Thus, commuting time seems relatively stable across periods of time for individuals in the sample. However, if we restrict the sample to individuals who have changed their job since the last survey period, Table 1 shows that the change rate in commuting time is 1.4 % for the average husband, and 6.6 % for the average wife.

Furthermore, it may be the case that individuals in the sample have experienced job changes that *increase* their wage (i.e., job changes with positive impact on their labor market outcomes), which may indicate that workers are willing to commute longer to earn the wage premium. Conversely, it may be that workers find a job closer to their home, and thus they may be willing to accept similar or lower salaries in exchange for shorter commutes. To provide a first exploratory analysis, we compare the change rate in commuting time subject to job changes that have a positive change in wages, and subject to job changes that have a negative change in wages.

[14] Table A1 in Appendix A presents summary statistics of demographic and labor outcomes, while Fig. A1 in Appendix A shows the density distribution of commuting times for husbands and wives, including individuals who both moved and did not move, and those who both changed jobs and did not change jobs.

[15] For completeness, Fig. A2 in Appendix A reports trends in average commuting duration in the US over the period 2003–2024, total, and by sex, using the American Time Use Survey data of the IPUMS (Flood et al., 2023).

[16] Of those who changed jobs, 49.6% of men and 46.3% of women also changed occupations. This means that about half of those who change jobs also shift occupations, while the other half change jobs within the same occupation. We return to occupations below.

[17] Among households that moved, 28.5% moved to homes with fewer rooms, 22.6% to homes with the same number of rooms, and 48.9% to larger homes. Thus, approximately half of moving households do so to acquire more space.

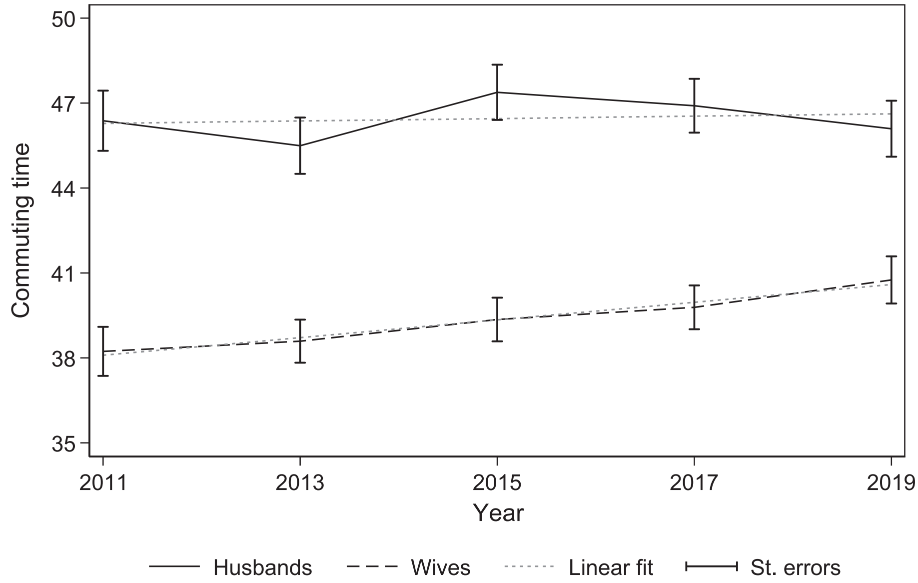

Fig. 2. Trends in household commuting times. Note: The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Averages computed using sample weights. Commuting time is measured in minutes per day.

Table 1 shows that husbands who change their job and experience a positive wage shock report an increase in their commuting time of about 6.7 %, whereas those who changed job and experienced a negative wage shock report a decrease in commuting time of about 4.3 %. Wives who report a job change and a positive (negative) wage shock report an increase in their commuting time of about 8.2 % (4.6 %).

Similarly, we explore the growth rate of commuting time conditional on moving. Table 1 shows that having moved relates to an increase in commuting time of about 6.0 % for husbands, and 8.7 % for wives. In other words, moving relates to increased commuting time of spouses for the average household in the sample. We also explore commuting when spouses have changed job and, simultaneously between survey waves, have moved. If these two events occur simultaneously, the husband's commuting time increases by about 11.2 % on average, while the average female commuting time increases by about 11.7 %.

To complement the results shown in Table 1, Fig. 3 shows density estimates of the growth rate of commuting time. Most of the individuals in the general population experience close to zero changes in commuting time, with a very large leptokurtic distribution around zero. Fig. 4 shows similar density estimates, conditional on job changes (Panel A), on job changes that generate positive and negative wage shocks (Panel B and Panel C, respectively), and on moving (Panel D). Fig. 4 shows that, once we condition a job change or a residential move, the variability of the growth rate of commuting time increases. Specifically, the growth rate in commuting time under job changes is quite symmetric, and thus the averages shown in Table 1 mask some degree of heterogeneity. A deep analysis of heterogeneity across households would require long time-series per household, which the PSID does not provide, and thus is left for further research using other sources of longitudinal micro-data.

5. Empirical strategy

We detail our econometric strategy to investigate how job changes impact the rate of change in commuting times for husbands and wives, considering observable and time-invariant unobservable factors, with a primary focus on discerning whether job changes lead to observable shifts in worker commuting times, net of changes in residence location. Our empirical model is as follows. For a given household i formed by a husband and a wife, $j = 1, 2$, respectively, with appropriate survey records during periods t and $t-1$, we estimate the following equations:

$$\Delta \text{logCommuting}_{it}^{j} = \alpha_i^j + \beta_1^j JC_{it}^j + \beta_2^j JC_{it}^{-j} + \beta_3^j JC_{it}^j JC_{it}^{-j} + \beta_X^j X_{it}^j + \alpha_t^j + \varepsilon_{it}^j, j = 1, 2.$$

Husband ($j = 1$) and wife ($j = 2$) equations are estimated simultaneously using fixed effects Seemingly Unrelated Regression (SUR) models (Zellner, 1962). Commuting_{it}^j represents the commuting time of spouse j of household i in period t, and thus $\Delta\text{logCommuting}_{it}^j$ represents the growth rate of j's commuting time between period t and period $t-1$. α_i^j is the household fixed effect, JC_{it}^j is a dummy that takes value 1 if spouse j of household i has changed his/her job between periods t and $t-1$, JC_{it}^{-j} is the equivalent for spouse $-j$ (i.e., j's partner), and $JC_{it}^j JC_{it}^{-j}$ captures the additional response generated when *both* spouses change their job at the same time.

We must control for the potential relationship between residential moving and commuting time. Without this control, we would face challenges disentangling whether variations in commuting times are attributed to residential mobility. However, controlling for moving may also be problematic, since residential moving may not only influence commuting but also trigger or result from job

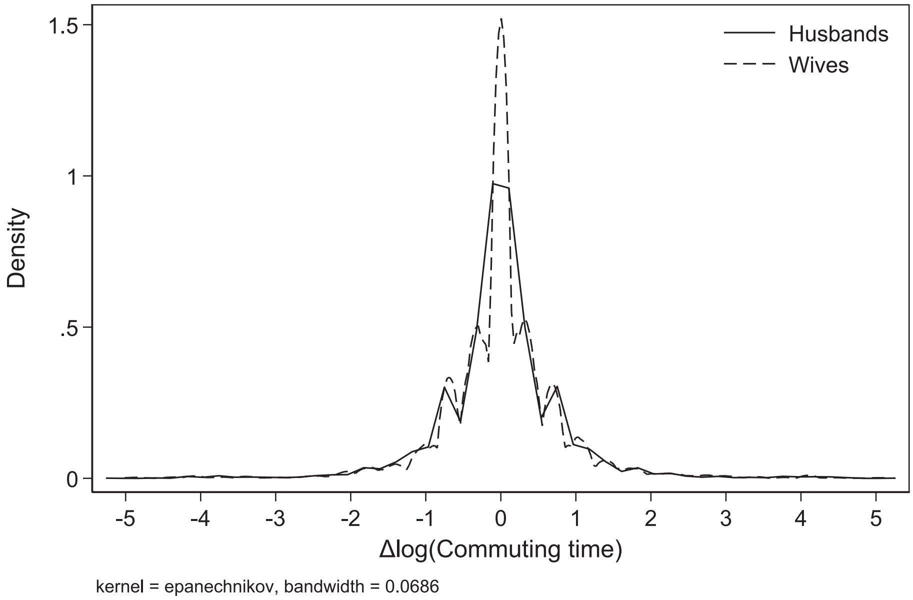

Fig. 3. Density of Δlog(commuting). Note: The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Commuting time is measured in minutes per day.

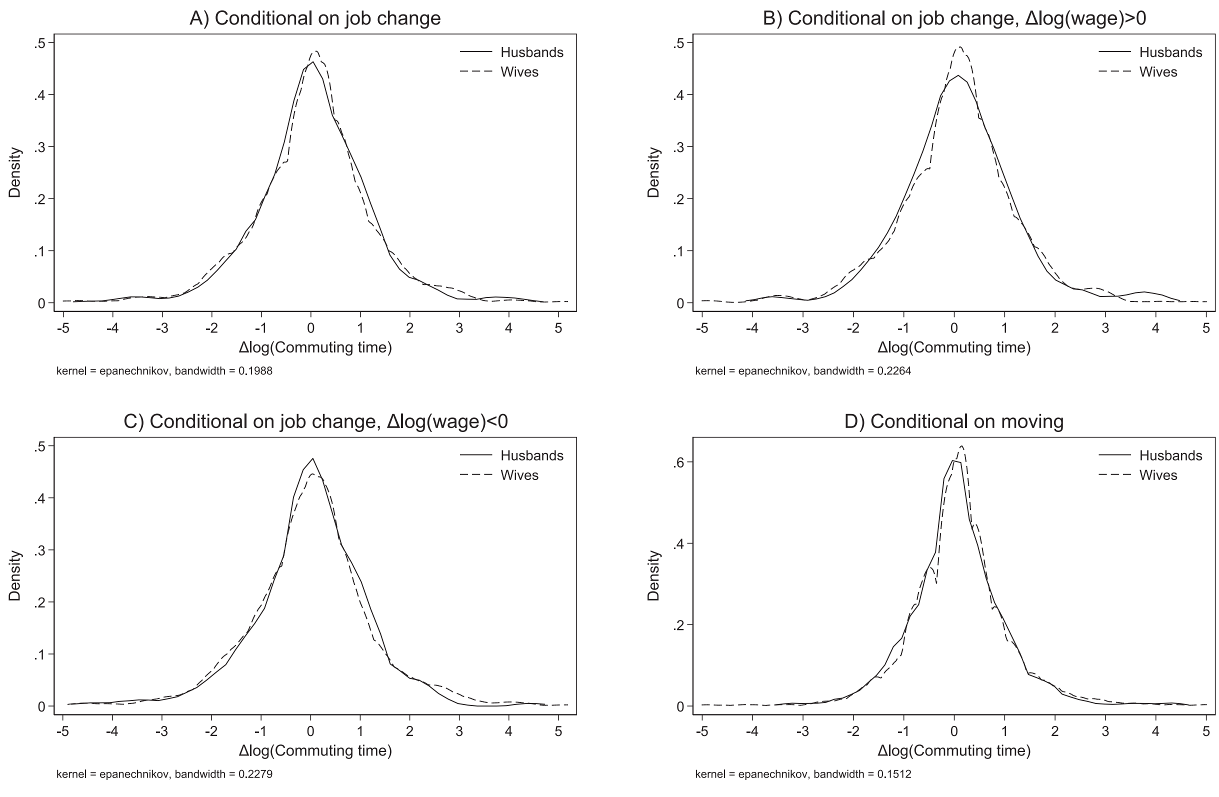

Fig. 4. Density of Δlog(commuting) conditional on events. Note: The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Commuting time is measured in minutes per day.

changes, and thus may be considered a bad control. We return to this point below.

We include controls for time-specific effects, occupation fixed effects, demographic characteristics of workers, and household fixed effects, encompassing observable and time-variant attributes of households.[18] X_{it}^{j} is a vector of demographics that are time-variant within households (whether the household moved between time periods, age and age squared, spouses' self-employment status, family size, number of children, the age of the youngest child, type of housing and tenure, number of rooms, family earnings, and number of available vehicles and changes in available vehicles). α_t^j represents year fixed effects, and ε_{it}^{j} is the error term.

It is noteworthy that commuting times may vary even when workers do not change jobs or relocate. Such changes can stem from factors like shifts in transportation modes, alterations in road infrastructure, weather conditions, adjustments in available commuting routes, or fluctuating congestion levels over time, among other potential influences.[19]

We estimate three additional models. First, we include occupation fixed effects, noting that not all workers who change jobs remain in the same occupation.[20] The PSID includes occupation codes, which have been harmonized based on the 2010 Occupation Code List of the US Census Bureau, including: 1) Management, Business, and Financial occupations. 2) Computer, Engineering, and Science occupations. 3) Education, Legal, Community Service, Arts, and Media occupations. 4) Healthcare Practitioners and Technical occupations. 5) Service occupations. 6) Sales and Related occupations. 7) Office and Administrative Support occupations. 8) Farming, Fishing, and Forestry occupations. 9) Construction and Extraction occupations. 10) Installation, Maintenance, and Repair occupations. 11) Production occupations. 12) Transportation and Material Moving occupations. 13) Military Specific occupations.

Second, we re-estimate equations differentiating between job changes that generate a *positive impact* (an increase) in wages, $JC_{it}^{j(+)}$, and job changes that generate a *negative impact* (a decrease) in wages, $JC_{it}^{j(-)}$. Thus, we can study whether a job change that drives an improvement in labor market conditions of spouses relates to spouses' commuting time differently than a job change that decreases the labor market outcomes of spouses. To do so, we estimate the following equations:

$$\Delta\text{logCommuting}_{it}^{j} == \alpha_i^j + \beta_1^j JC_{it}^{j(+)} + \beta_2^j JC_{it}^{-j(+)} + \beta_3^j JC_{it}^{j(-)} + \beta_4^j JC_{it}^{-j(-)} + \beta_X^j X_{it}^j + \alpha_t^j + \varepsilon_{it}^j, \quad j = 1, 2$$

where all the terms are defined as previously.

It is crucial to highlight that the PSID dataset lacks the necessary sample size for examining potential heterogeneity by estimating equations on a household-by-household basis. Factors such as variations in the number of children, changes in household composition, access to a car, alterations in domestic responsibilities, and differences in worker ages may act as mechanisms moderating the correlation between job changes and commuting times. For example, a job change leading to reduced commuting time for one worker could result in increased leisure time and more opportunities for household chores and caregiving. Consequently, this shift may potentially relieve the partner of such responsibilities while simultaneously allowing them to invest more time in commuting in pursuit of an improved job opportunity.

Although we cannot provide a deep study of heterogeneity household by household, we do analyze potential heterogeneity by estimating possible underlying mechanisms behind the estimated conditional correlations. In doing so, we estimate the following equations:

$$\begin{aligned}\Delta\text{logCommuting}_{it}^{j} &= \alpha_i^j + \beta_1^j JC_{it}^{j} + \beta_2^j JC_{it}^{j} \times \text{event}_{it}^j + \beta_3^j JC_{it}^{-j} + \beta_4^j JC_{it}^{-j} \times \text{event}_{it}^j + \beta_5^j JC_{it}^{j} JC_{it}^{-j} + \beta_6^j JC_{it}^{j} JC_{it}^{-j} \times \text{event}_{it}^j + \beta_X^j X_{it}^j + \alpha_t^j \\ &\quad + \varepsilon_{it}^j, \quad j \\ &= 1, 2,\end{aligned}$$

where the variable event_{it}^j captures some individual or household characteristic also included as part of X_{it}^j, namely age cohorts, or the number of children, and the remaining terms are defined as in the previous equations. Thus, coefficients β_1^j, β_3^j and β_5^j capture the correlation between job changes and commuting time growth for the general population (i.e., for those who do not experience the event), and β_2^j, β_4^j and β_6^j allow us to analyze if individuals who experienced said event experience some additional correlation (beyond that captured by the coefficients for the general population).

A crucial consideration in our entire identification strategy is the control for households' residence location between survey records, along with both observable and unobservable household characteristics. However, our approach precludes estimating causal effects, due to the lack of information on the exogeneity of job changes, such as firm-initiated relocations impacting commuting times. Unfortunately, the PSID lacks specific details to distinguish voluntary job changes (e.g., pursuing a better opportunity) from those compelled by external factors (e.g., job loss followed by reemployment). Despite this limitation, our analysis allows us to identify a conditional correlation, offering insights into how spouses' commuting time responds to job changes within the available data context.

[18] There are alternative paths to study the relationship between job changes and worker commuting time. For instance, one could estimate a structural job search model including commuting time, as in van Ommeren et al. (1997, 1999). However, it is unclear how such a job search model could be formulated in a household context, rather than in an individual context.

[19] Spouses' education, race, immigrant status, and State fixed effects are omitted because they are time-invariant within households, and as such their potential effects are captured by the household fixed effects. Spousal age is omitted because of matching trends in the US marriage market (Chiappori et al., 2020).

[20] We do not include occupation fixed effects in our baseline specification, as these effects may capture part of the relation of interest for the individuals who changed their occupation when changing their job.

6. Results

6.1. Job changes and the growth rate of commuting time

Table 2 shows the main coefficients of SUR fixed effects models. Columns (1) and (2) show the main estimates of the baseline model on husbands and wives, respectively. Columns (3) and (4) show results when controlling for occupation fixed effects. On one hand, the results show that a job change of the husband is related to a decrease in his commuting time, with that decrease ranging between 14.9 % and 15.4 %, and the coefficients are statistically significant at standard levels across specifications. On the other hand, husbands' commuting growth rate seems not to depend on whether only the wife has changed her job. Despite that, if both the wife and the husband change their jobs between the same time periods, husbands experience a significant increase in their commuting time of between 26.2 % and 27.6 %. The growth rate of wives' commuting seems not to be sensitive to their own and the partner's job changes, regardless of whether these changes are simultaneous or not. Furthermore, residential moving is consistently related to increases in commuting time for both husbands and wives. Specifically, residential moving is related to increases of between 8.4 % and 8.9 % in the husband's commuting time, and between 21.4 % and 21.9 % in the wife's.

These findings highlight distinct commuting time dynamics in response to job changes and residential moving for husbands and wives. Notably, a husband's job change is consistently linked to a significant reduction in his commuting time. However, husbands' commuting time growth rate remains unaffected when only the wife changes her job. Simultaneous job changes by both partners, however, result in a substantial increase in husbands' commuting time. Wives, regardless of their own or their partner's job changes, exhibit an insensitive commuting time growth rate. Additionally, residential moving consistently correlates with commuting time increases for both husbands and wives. These patterns shed light on the intricate relationship between employment changes, residential mobility, and spouses' commuting times within households.

Regarding the remaining coefficients, which are shown in Appendix Table A2, the study reveals a connection between spouses' self-employment status and changes in commuting time. Self-employed husbands and couples experience higher growth rates in commuting than employees, while self-employed wives tend to have smaller changes in commuting time. Household composition does not appear to be correlated with the growth rate of commuting time, despite prior research indicating its association with worker commuting time (Lee and McDonald, 2003; Roberts et al., 2011; Carta and De Philippis, 2018). Living in a house, as opposed to an apartment or flat, is also associated with a decreased commuting time growth rate. Interestingly, husbands (but not wives) who own their homes tend to experience larger changes, potentially influenced by the increased moving costs for homeowners compared to those living in rented homes. Finally, the number of vehicles relates positively to the husband's change in commuting time, while changes in the number of vehicles (i.e., more vehicles available for commuting) relates negatively to spouses' commuting time, although the coefficients are marginally significant only.

6.2. Job changes and shocks to wages

Table 3 shows the main results of the specification in which we differentiate between job changes that generate positive shocks to wages, and job changes that generate negative shocks to wages. Additional coefficients are shown in Table A3 in the Appendix. Column

Table 2
Fixed effects joint estimates.

	Baseline		Occupation F.E.	
	(1)	(2)	(3)	(4)
Variables	Husbands ($j = 1$)	Wives ($j = 2$)	Husbands ($j = 1$)	Wives ($j = 2$)
Job change of j	−0.154***	0.058	−0.149***	0.046
	(0.039)	(0.038)	(0.039)	(0.037)
Job change of $-j$	−0.008	−0.029	−0.004	−0.034
	(0.037)	(0.040)	(0.037)	(0.039)
Job change of j & $-j$	0.416***	0.011	0.425***	0.024
	(0.069)	(0.071)	(0.069)	(0.071)
Moved	0.084**	0.219***	0.089**	0.214***
	(0.037)	(0.038)	(0.037)	(0.038)
Demographics	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Occupation fixed effects	No	No	Yes	Yes
Observations	5,443	5,443	5,443	5,443
R-squared	0.352	0.332	0.356	0.341

Note: Robust standard errors clustered at the household level in parentheses. The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Estimates computed using sample weights. The dependent variable is the change in the log of commuting time, Δlog(commuting). Additional coefficients shown in Table A2 in the Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

Table 3
Job changes and the sign of wage shocks.

Variables	(1) Husbands ($j = 1$)	(2) Wives ($j = 2$)
Job change of j | Δlog(wage$_j$) > 0	−0.162***	0.107**
	(0.047)	(0.044)
Job change of j | Δlog(wage$_j$) < 0	−0.145***	−0.001
	(0.047)	(0.047)
Job change of $-j$ | Δlog(wage$_{-j}$) > 0	−0.015	−0.024
	(0.043)	(0.048)
Job change of $-j$ | Δlog(wage$_{-j}$) < 0	0.001	−0.031
	(0.046)	(0.048)
Demographics	Yes	Yes
Household fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	5,443	5,443
R-squared	0.352	0.333

Note: Robust standard errors clustered at the household level in parentheses. The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Estimates computed using sample weights. The dependent variable is the change in the log of commuting time, Δlog (commuting). Additional coefficients shown in Table A3 in the Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

(1) shows estimates on husbands, and Column (2) shows the main coefficients for wives. We observe that a job change that entails a wage increase relates to a decrease of about 16.2 % in husband commuting time, while a job change that decreases the wage relates to a decrease of about 14.5 % in his commuting time. These coefficients are not different, according to a t-type test ($p = 0.798$). The correlations between joint job changes and moving, on the one hand, and husband commuting time growth rate, on the other hand, remain similar to the baseline estimates in Table 2. The results suggest that the sign of the wage shock experienced by husbands when changing jobs is not relevant in determining the change in commuting time, as coefficients are both negative and highly significant.

Regarding results for wives' growth rate of commuting time, estimates show that commuting time on average increases by about 10.7 % if they experience a job change that entails a wage increase. Conversely, wives' job changes that relate to a decrease in wages do

Table 4
Partial effects heterogeneity.

	(1)	(2)	(3)	(4)
	Husbands ($j = 1$)		Wives ($j = 2$)	
Variables	Partial effect	St. Error	Partial effect	St. Error
A. By age cohorts				
Job change of j | boomer	−0.356***	(0.066)	0.046	(0.077)
Job change of j | gen X	0.022	(0.039)	0.102***	(0.006)
Job change of j | millenial	−0.166***	(0.029)	−0.010	(0.006)
Job change of $-j$ | boomer	0.084	(0.069)	−0.073	(0.069)
Job change of $-j$ | gen X	−0.020**	(0.010)	−0.039***	(0.005)
Job change of $-j$ | millenial	−0.052***	(0.015)	0.024**	(0.010)
Job change of j & $-j$ | boomer	0.244	(0.177)	0.183	(0.169)
Job change of j & $-j$ | gen X	0.349***	(0.048)	0.090**	(0.035)
Job change of j & $-j$ | millenial	0.479***	(0.067)	−0.111*	(0.067)
B. By the presence of kids under 5 years				
Job change of j | no kids under 5	−0.167***	(0.043)	0.099**	(0.042)
Job change of j | kids under 5	−0.121***	(0.008)	−0.091***	(0.016)
Job change of $-j$ | no kids under 5	0.029	(0.041)	−0.020	(0.044)
Job change of $-j$ | kids under 5	−0.136***	(0.014)	−0.082***	(0.006)
Job change of j & $-j$ | no kids under 5	0.396***	(0.081)	0.082	(0.083)
Job change of j & $-j$ | kids under 5	0.491***	(0.035)	−0.076***	(0.025)
Observations	5,443		5,443	

Note: The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Estimates computed using sample weights. The dependent variable is the change in the log of commuting time, Δlog(commuting). Boomers defined as those born before 1965. Gen X defined as those born between 1965 and 1980. Millenials defined as those born after 1980. Coefficient estimates shown in Table A4 in the Appendix. *** significant at 1 %; ** significant at 5 %; * significant at 10 %, with standard errors clustered at the household level computed using the Delta method in parentheses.

not relate to changes in their commuting time. Similarly, husbands' job changes are not related to the wife's commuting time. The correlation between moving and wives' commuting time growth rate remains as in the baseline results. Interpreted through our conceptual framework, these patterns indicate that wives accept longer commutes only when offset by wage gains, whereas husbands use job changes to shorten commutes regardless of the wage shock. This behavioral asymmetry is consistent with gendered constraints and intra-household bargaining highlighted in Sections 2.3 and 3.

6.3. Heterogeneity

We study whether age and household composition moderate the correlations between spouses' job changes and their commuting time growth rate. We focus first on potential differences in terms of age cohorts, dividing the sample into "boomers" (those born before 1965), "gen X" individuals (those born between 1965 and 1980), and "millennials" (those born after 1980). Table 4 shows the partial effects of job changes on commuting time growth rate, that is to say, the partial derivatives of the commuting time growth rate with respect to job changes for the analyzed population groups. Estimation details are shown in Table A4 in the Appendix. Standard errors shown in Table 4 are computed using the Delta method.

The results indicate significant variability in response to job changes among different demographic groups. Both older (boomer) and younger (millennial) husbands tend to reduce their commuting time when changing jobs, whereas middle-aged husbands show no significant variation. Wives' job changes do not impact commuting time for boomer couples, but for gen X and millennial couples, there are small yet statistically significant decreases in husband commuting time. Joint job changes lead to substantial increases in commuting time. The findings suggest that both older and younger husbands aim to decrease their commuting times, while middle-aged workers may not share this objective. Among wives, job changes are associated with increased commuting time only for middle-aged, gen X wives. The correlation between job changes and commuting time growth rate for boomer and millennial wives is not statistically significant. Differences in preferences for work and time allocations, or varying needs, may explain these patterns. For example, young wives may prioritize better jobs even with longer commuting times, or they may change jobs to care for children, seeking shorter commutes. Gender differences are further explored in the discussion section.

We next examine whether the presence of kids potentially moderates the correlations between job changes and commuting time, dividing the sample into those who have a kid under 5 years old and those who do not. For husbands, job changes relate to decreased commuting time in general terms, regardless of the presence of children. However, wife job changes relate to decreased husband commuting time only if the couple has a kid under 5 years old. Regarding wives' commuting time growth rate, the results reveal that a job change translates into an increase in her commuting if the couple does not have a kid under 5 years, but conversely into a decrease in her commuting if the couple does have a kid under 5. These results are consistent with time-allocation constraints within couples. With a child under 5, wives' commutes shorten and husbands adjust their own commuting when the wife changes job, pointing to caregiving-driven reoptimization. This suggests that relaxing childcare constraints could mitigate the asymmetric commuting responses documented here.

The findings suggest a shift in household responsibilities towards husbands, who seek shorter commutes when their wives start new jobs, to allocate more time to childcare. The positive and highly significant correlation between joint job changes and husband commuting time persists. Young children impact the relationship between wives' job changes and commuting time, aligning with the household responsibilities hypothesis. Women with kids prioritize shorter commutes for caregiving, while those without children pursue specialized or higher-paying positions, even with longer commutes. Changes in the husband's job and simultaneous job changes for both spouses result in decreased wives' commuting time only when the couple has kids under 5, supporting the household responsibilities hypothesis.

7. Discussion

We now present a comprehensive discussion of the findings, considering factors such as gender differences, robustness and sample selection. Specifically, we discuss the results for husbands and wives, and explore the potential endogeneity between residential moving, job changes, and commuting time, examining short- and mid-term correlations. Furthermore, we draw comparisons between our results and existing research.

Gender differences. Our analysis unveils distinct patterns by gender, providing insights into the intra-household dynamics of commuting time. Notably, our results for husbands demonstrate a significant correlation between job changes and the growth of their commuting time. Specifically, when husbands undergo job transitions (while wives do not) in two separate time periods, there is a considerable reduction in their commuting time. This implies a deliberate preference among husbands to pursue job opportunities closer to home, thereby mitigating their daily commuting burden. That is to say, this decision of reducing commuting time could reflect a desire to minimize the negative impacts of commuting on their quality of life (e.g., husbands may prioritize reducing commuting time to improve their wellbeing and health), seeking jobs that involve more convenient commuting times (Sandow and Westin, 2010).

However, if both the husband and wife change jobs between time periods, the husband's commuting time increases significantly, even after accounting for potential residential relocations. This finding is intriguing, especially given past research that suggested husbands' employment traditionally influenced wives' job searches (Madden, 1981), a topic we revisit later in the discussion. The simultaneous job change of both spouses might reflect a situation where household coordination or economic opportunities come into play, and the household as a whole might be willing to accept longer commutes for the husband in exchange for a more significant benefit, such as both partners finding better-paying or more specialized jobs. Then, this increase in commuting time could reflect a willingness to sacrifice convenience for higher wages or professional specialization.

The scenario for wives presents a contrasting perspective. Wives' commuting time seems not to be related to job changes in general terms, perhaps implying that wives are less likely to adjust their commuting time when changing jobs, maybe due to household responsibilities, which make female workers not try to avoid the negative consequences when they change jobs. However, the correlation is positive only if the job change entails a better wage, that is, if a potential new job relates to increased wages, wives are willing to accept it even if the commuting time increases, i.e., wives may prioritize the positive effects of longer commutes rather than the negative consequences. This may indicate wives pursue higher salaries when changing jobs, even if they opt for positions that require longer commuting times, prioritizing it over the potential negative consequences of commuting. This trend aligns with prevailing theories suggesting that women have increasingly sought more specialized job opportunities that often require longer commutes (Green, 1997; McQuaid and Chen, 2012).

However, our findings also reveal that wives experiencing job changes resulting in lower wages do not necessarily reduce their commuting time. This stands in contrast to results observed in France by Le Barbanchon et al. (2021), who conclude that women are willing to accept lower wages in exchange for shorter commutes (though measured in distance). Due to the absence of information on the reasons for job changes in the PSID data, we could not delve deeper into this result. It is plausible that job changes may encompass situations in which a wife loses her job, experiences a period of unemployment, and then secures new employment between time periods. This transition is captured as a job change due to the timing of the PSID data and differs significantly from a job-search perspective, compared to situations where someone secures a new job.

In addition to these correlations, our results do not reveal cross-correlations for wives. In other words, husbands' job changes do not appear to have a general impact on wives' commuting times. Possible explanations for this absence of correlation may be rooted in the household responsibilities hypothesis, involving childcare responsibilities, pregnancy, the presence of young children in the household, and similar factors. We conduct a partial exploration by considering heterogeneity in terms of the presence of young children and age cohorts. This analysis reveals more cross-correlations between spousal job changes and individual commuting times, although it remains suggestive evidence only, due to the unknown reasons behind job changes in the PSID. Nevertheless, the identification of cross-correlations, especially among younger couples and those with kids under 5 years, suggests that household characteristics may drive potential cross effects between spouses' job changes and commuting times.

Other potential mechanisms could include carpooling, shifts in travel modes prompted by job changes, alterations in the timing of commuting related to rush hours and traffic congestion, or improvements in the timing and synchronization of commutes (Oakil et al., 2016). However, a more comprehensive investigation into these channels requires specific data not currently available in the PSID dataset, such as information on vehicle ownership, time allocation, distance, and commuting patterns.

Despite these limitations, our results provide some insights on how some life events impact the dynamics of household commuting time. Specifically, estimates suggest that residential relocation relates to increased commuting time among both the wife and the husband, although the impact seems quite larger among wives, while only limited among husbands. Job changes of the husband do not seem to have a cross impact on household commuting dynamics, as they only relate to the husband's commuting time, while the job change of wives relates to the husbands' commuting through joint job changes, indicating an impact on intrahousehold dynamics. As a consequence, further research should investigate potential intrahousehold mechanisms that explain such cross impact.

Finally, the negative correlation estimated between residential relocation and male and female commuting time may be explaining by several factors. For example, households may search for better amenities typically in the city's periphery, prioritize non-commute factors when moving (their preferences for housing are stronger than those for shorter commutes), or take balanced decisions that

Table 5
Robusntess checks.

	Without "moved" control		Excluding movers	
	(1)	(2)	(3)	(5)
Variables	Husbands ($j = 1$)	Wives ($j = 2$)	Husbands ($j = 1$)	Husbands ($j = 1$)
Job change of j	−0.151***	0.055	−0.167***	0.062
	(0.039)	(0.038)	(0.044)	(0.040)
Job change of $-j$	−0.009	−0.023	0.009	−0.063
	(0.037)	(0.040)	(0.042)	(0.042)
Job change of j & $-j$	0.429***	0.044	0.324***	−0.045
	(0.069)	(0.071)	(0.091)	(0.087)
Moved	–	–	–	–
Demographics	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	5,443	5,443	4,191	4,191
R-squared	0.351	0.328	0.375	0.404

Note: Robust standard errors clustered at the household level in parentheses. The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Estimates computed using sample weights. The dependent variable is the change in the log of commuting time, Δlog(commuting). Additional coefficients shown in Table A5 in the Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

ultimately impact commuting time positively (e.g., Blumenberg and King, 2019). It may also indicate that the new location offers access to better job markets in the mid run, which may entail future job changes. We explore some of these potential channels below.

Robustness checks. We conduct two robustness tests to investigate potential selection and endogeneity biases in our study. Specifically, the relationships among commuting time, residential moving, and job changes are likely endogenous, with residential moving possibly triggering job changes, and vice versa, as discussed above (see Jang and Yi, 2021). This creates a situation where individuals experiencing job changes may either stay in their current residence (stayers) or move to a new location. Consequently, the act of moving can be an outcome of a job change, potentially serving as a flawed control variable and introducing selection bias into our estimates of interest. To address this concern, we narrow the sample to stayers, individuals who did not relocate between the observed time periods. The estimates, presented in Table 5, demonstrate the robustness of our conclusions compared to the baseline results in Table 2. This suggests that endogeneity between residential relocation and job changes is likely not to affect the conclusions drawn from the baseline analysis.

Second, and building upon the earlier point, we examine the potential endogeneity between job changes and residential moving by investigating whether job changes lead to future residential relocations (within the next two years) and vice versa. Table 6 presents summary statistics for concurrent events, such as simultaneous job changes and job changes coinciding with residential moving, as well as events occurring two years prior that subsequently trigger other events at the current date. The averages indicate that the proportion of households in which job changes prompt residential relocations in the next two years is minimal. For example, among the 18.3 % (20.4 %) of husbands (wives) who underwent job changes in the past two years, only 4.9 % (5.4 %) initiated a residential move. Conversely, 23.5 % of households reported moving in the previous two years, leading to a job change for 7.3 % of husbands and 7.9 % of wives in the sample. While summary statistics imply that job changes may trigger residential moves for some households, they also suggest that this is not a prevailing trend.[21] Again, this suggests that the key results are likely not affected by endogeneity regarding job changes triggering residential relocation in the near future, and vice versa.

Short-term correlations. Another constraint in our analysis pertains to the temporal aspect of the data, primarily capturing short-term correlations between job changes and commuting time. It is possible that, following a job change, individuals may temporarily experience longer commutes as they navigate the housing market for potential relocation. While the main empirical analysis accounts for such reallocations if identified during the PSID interviews, there is a limitation in capturing events that may occur further in the future, leading to potential bias. In essence, the estimated correlations may be influenced by the timing of the data rather than reflecting structural correlations. To partially mitigate this concern, we re-evaluate the main equations by incorporating job changes and residential moving not only at date t but also at date $t-2$ (i.e., job changes and residential moving during the previous PSID wave).

Table 7 presents the estimates, indicating that job changes and residential moving in the past are not significantly linked to spouses' commuting time. This suggests that the biennial frequency of the survey sufficiently captures the structural correlation between job changes and residential moving, on one hand, and the growth rate of spouses' commuting time, on the other hand, at least in the short- and mid-term. Examining these correlations over the long term would necessitate extensive time series data per household, a limitation not met by the PSID dataset. Therefore, we reserve such analysis for future research and acknowledge that our results are confined to capturing short- and mid-term correlations exclusively.

Relation to previous results. Our findings regarding wives align with the conclusions drawn by van Ommeren et al. (1997, 1999) in the Netherlands, who observed increased commuting distance among workers offered better-paid jobs. This also aligns with recent analyses by Sprumont et al. (2014), Yang et al. (2017), Rau et al. (2019), and Hrehová et al. (2023), who find a positive correlation between job relocation and commuting time. Our estimates suggests that, among husbands, job changes relate to decreased commuting, indicating a preference for shorter commutes, and that progress through husbands' employment careers corresponds to decreased commuting time. This contrasts with the estimates for wives, but is in line with estimates by von Behren et al. (2018) and Pritchard and Frøyen (2019). Furthermore, the differential results for wives and husbands may indicate different preferences for looking for workplaces in the city centre or in the cities' periphery. Unfortunately, the PSID does not include the information for a deeper analysis.

In addition, we do not find an impact of spousal job changes on commuting time, neither in general terms nor when differentiating the change in wages when changing jobs, which aligns with the results by Morris and Zhou (2018) in China, who concluded that spousal wages did not relate to changes in one's commuting, and by Ghasri and Rashidi (2019) who find that spouses' commuting times are individual decisions in Australia. However, our estimates suggest that joint job changes relate to increased commuting time for husbands, but do not relate to changes in commuting among wives. This result highlights the importance of considering the spouse when analyzing commuting time, and also indicates the relevance of life events that may occur jointly.

Besides this, while van Ommeren et al. (1997) propose that correlations between job changes and commuting may be temporary and linked to future residential moves, our US estimates suggest otherwise, at least in the mid-run (i.e., years t and t – 2). Unfortunately, the PSID does not allow for a more extended observation of households over consecutive time periods to study whether these results hold over a worker's lifecycle or employment career. Additionally, the correlation may be influenced by intrahousehold dynamics, where a wife's wage increase may enhance her bargaining power, potentially leading to a shift in household resources in the mid-run, such as gaining access to the household car or decreased childcare responsibilities—factors not captured in our analysis.

Finally, our results indicate that residential moving is associated with increased commuting time for both husbands and wives, with this result being robust for the specifications estimated. Potential explanations for this result may stem from urban forms in the US,

[21] We focus on events at dates $t-2$ and t because of the biennial nature of the data. Showing summary statistics in a longer-run (i.e., focusing on $t-4$) would result in substantial sample size cuts.

Table 6
Details on moving and job changes.

	Mean	S.Dev.
Simultaneous events (N = 5,443)		
Husband and wife changed job at date t	0.068	0.252
Husband changed job at t and the household moved at date t	0.061	0.240
Wife changed job at t and the household moved at date t	0.066	0.248
Husband and wife changed job at date t, and moved at date t	0.033	0.180
Job change of the husband at date $t-2$ (N = 2,904)	0.183	0.387
triggers a job change of the wife at date t	0.046	0.210
triggers moving at date t	0.049	0.215
triggers a job change of the wife at date t and moving at date t	0.019	0.137
A job change of the wife at date $t-2$ (N = 2,904)	0.204	0.403
triggers a job change of the husband at date t	0.049	0.216
triggers moving at date t	0.054	0.226
triggers a job change of the husband at date t and moving at date t	0.019	0.136
Moving at date $t-2$ (N = 5,443)	0.235	0.424
triggers a job change of the husband at date t	0.073	0.260
triggers a job change of the wife at date t	0.079	0.269
triggers a job change of both spouses at date t	0.035	0.184

Note: The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Statistics computed using sample weights.

Table 7
Non-short-term effects.

	(1)	(2)
Variables	Husbands ($j=1$)	Wives ($j=2$)
Job change of j at date t	−0.233***	0.091*
	(0.057)	(0.054)
Job change of j at date $t-2$	−0.014	0.018
	(0.056)	(0.055)
Job change of $-j$ at date t	−0.028	−0.044
	(0.051)	(0.060)
Job change of $-j$ at date $t-2$	0.016	0.042
	(0.052)	(0.059)
Job change of j & $-j$ at date t	0.306***	−0.013
	(0.107)	(0.113)
Job change of j & $-j$ at date $t-2$	−0.042	0.022
	(0.104)	(0.110)
Moved at date t	0.043	0.104*
	(0.054)	(0.057)
Moved at date $t-2$	−0.051	0.052
	(0.054)	(0.057)
Demographics	Yes	Yes
Household fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	2,904	2,904
R-squared	0.384	0.373

Note: Robust standard errors clustered at the household level in parentheses. The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Estimates computed using sample weights. The dependent variable is the change in the log of commuting time, Δlog(commuting). Additional coefficients shown in Table A6 in the Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

where households typically seek better amenities when moving, often located in the city outskirts (Blumenberg and King, 2019). In contrast, urban patterns in other countries may differ, influencing commuting dynamics (Brueckner et al., 1999). This result is consistent with previous analyses on the relationship between residential relocation and commuting, as moving relates to increased commuting distance in the US (Blumenberg and King, 2019), and also in other countries (Akbari and Habib, 2018). However, our results contrast with Clark et al. (2003) who investigated the specific case of Seattle, perhaps because of the specific case scenario of the analysis (e.g., Seattle specific urban form or the built environment) compared to the general case of the US.

8. Conclusions

This study examines the correlations between job changes and commuting time for husbands and wives, accounting for residential relocations, household-specific factors, and unobserved heterogeneity, utilizing data from the PSID spanning the period 2011–2019. Fixed-effects estimations yield several significant findings regarding the intricate interplay between job changes and the dynamics of commuting times within households.

When husbands change jobs, a discernible reduction of approximately 15 % is observed in their commuting time. In contrast, when wives experience job changes accompanied by a wage increase, their commuting time rises by around 11 %, with no notable impact on commuting time for other job changes. Simultaneous job changes by spouses in the same time period coincide with a substantial increase in husband commuting time, approximately 27 %. Heterogeneity in these correlations is further unveiled concerning household composition and worker age. These findings contribute to the existing literature by exploring the dynamics of commuting time within households, a dimension that has been previously underexplored due to the limited availability of household panel surveys with detailed information on commuting times.

Our estimates indicate that households re-optimize commuting around job changes in gender-specific ways, with marked gender asymmetries, and that residential moves in the US are associated with higher commuting times in the short-to-mid term. Furthermore, our results also suggest that childcare constraints modulate these patterns. In this context, improving job-housing balance and transit accessibility may curb the commuting increases associated with residential moves; employer policies that expand telework and flexible scheduling can accommodate longer commutes following wage-increasing job changes; and childcare support can reduce the unequal adjustments around wives' job changes.

Despite the valuable insights gained, several limitations should be acknowledged. First, the PSID's measurement of commuting time relies on stylized questions, potentially introducing measurement errors, compared to more detailed time-use diaries. Second, the absence of information on commuting distance, transportation modes, or carpooling limits our exploration of these aspects of household commuting behavior. Specifically, commuting distance and commuting mode affect commuting time, and as a consequence, our results cannot disentangle the underlying reasons behind changes in commuting time. Third, the dataset's limited availability of uninterrupted time series per household hinders a comprehensive analysis of the potential long-term correlation between job changes and commuting time in the context of future residential relocations. Fourth, the absence of data on specific reasons for job changes impedes addressing potential endogeneity. Relatedly, the PSID lacks information on whether job changes trigger residential moving or vice versa, preventing the identification of causal links, thus rendering our findings as conditional correlations despite adjusting for observed and unobserved heterogeneity.

Despite these limitations, our study provides several important insights with significant policy implications, particularly concerning commuting behaviors, telecommuting, and urban planning. Policies that encourage hybrid or remote work arrangements can help mitigate the gendered effects of commuting, where women are more likely to endure longer commutes for higher wages. By promoting telecommuting, workers, especially women, would gain greater flexibility in balancing job opportunities and commuting burdens. Governments could support these efforts through tax incentives for employers in sectors where remote work is feasible, which would not only reduce transportation costs and alleviate congestion but also contribute to more sustainable urban development. Furthermore, investing in digital infrastructure, such as high-speed internet, is essential to ensure remote work can be effectively integrated, particularly in suburban or rural areas.

From an urban planning perspective, planners should prioritize the development of non-centralized cities and residential areas with better proximity between employment centers and housing. This approach would benefit families by reducing commuting burdens, especially for husbands who tend to have shorter commutes. Additionally, expanding and improving public transportation infrastructure, particularly in dense urban areas where origins and destinations are close allowing for reasonable travel times, would help make longer commutes more feasible and less stressful for both spouses. While our study does not analyze commuting modes directly, the evidence from urban planning suggests that improving public transit services, particularly in dense urban areas, would help mitigate some of the increased commuting times observed with relocation. Increased frequency and connectivity, especially during peak hours, would help reduce the reliance on private vehicles and improve overall commuting efficiency.

In recognition of the evolving dynamics of dual-career couples, policies should also be implemented to address their unique needs. These could include dual-job placement services, childcare support, and spousal job-search assistance, enabling both partners to pursue fulfilling careers without compromising family wellbeing. Alongside this, recruitment policies must be updated to be more gender-inclusive, taking into account each partner's career aspirations independently, as husbands' job changes no longer exclusively dictate wives' job searches.

Addressing wage disparities is another crucial area. Women's willingness to endure longer commutes for higher salaries suggests the need to ensure equitable pay for comparable roles, thus reducing the need for such trade-offs. Urban planning should also encourage balanced city development, focusing on creating residential areas with good access to employment centers, which would benefit both genders by reducing commuting times and improving overall quality of life. Finally, to support more targeted policy interventions, comprehensive data collection on commuting behaviors—including commuting distance, transportation modes, and reasons for job changes—would provide a deeper understanding of commuting patterns and inform effective policy-making.

CRediT authorship contribution statement

José Ignacio Giménez-Nadal: Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **José Alberto Molina:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Jorge Velilla:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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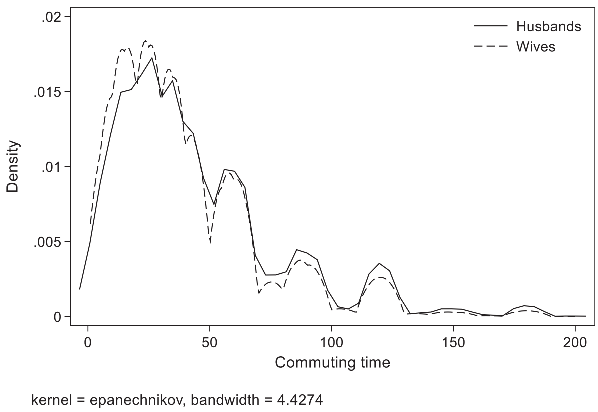
Declaration of competing interest

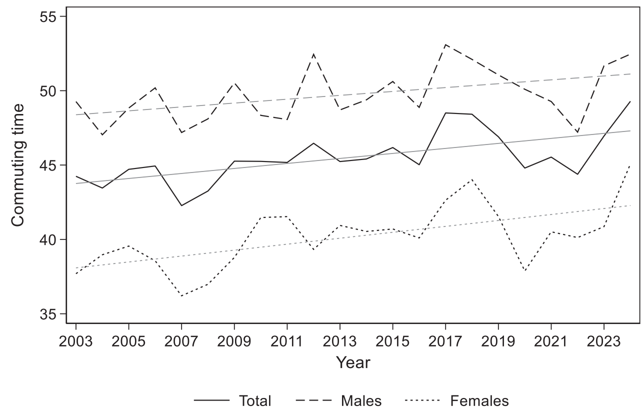
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A:. Additional results



Note: The sample (PSID 2011-2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Commuting time is measured in minutes per day.

Fig. A1. Density of commuting time. Note: The sample (PSID 20112019) is restricted to two-member stable households with positive labor supply in consecutive periods. Commuting time is measured in minutes per day.



Note: The sample (ATUS 2003-2021) is restricted to employed workers who commute to/from work. Averages computed using sample weights. Commuting time represents the time spent commuting to and from work, and is measured in minutes per day.

Fig. A2. Trends in commuting time in the US. Note: The sample (ATUS 20032021) is restricted to employed workers who commute to/from work. Averages computed using sample weights. Commuting time represents the time spent commuting to and from work, and is measured in minutes per day.

Table A1
Summary statistics of demographics.

Variables	Husbands ($j = 1$)		Wives ($j = 2$)		Difference (*husband – wife*)	
	Mean	S.Dev.	Mean	S.Dev.	Diff.	*p*-value
Demographics:						
Age	44.606	10.834	43.035	10.663	1.572	0.000
Basic education	0.082	0.275	0.045	0.208	0.037	0.000
Secondary education	0.265	0.441	0.202	0.401	0.063	0.000
College education	0.463	0.499	0.495	0.500	−0.032	0.000
Higher education	0.190	0.392	0.258	0.438	−0.068	0.000
White	0.061	0.375	0.829	0.376	0.001	0.839
Black	0.079	0.270	0.068	0.252	0.011	0.008
Labor market outcomes						
Hours of work (/1,000)	2.186	0.591	1.794	0.614	0.392	0.000
Hourly wage	34.629	29.593	26.542	22.235	8.087	0.000
Self-employed	0.089	0.284	0.054	0.227	0.034	0.000
Households						
			Mean	S.Dev.		
Immigrant household			0.136	0.342		
Family size			3.276	1.213		
Number of children			1.016	1.152		
Age of youngest child			3.884	5.215		
Housing type: house			0.847	0.360		
Number of rooms			6.519	2.282		
Tenure: home owned			0.804	0.397		
Family income (/1,000)			134.004	98.908		
Number of vehicles			2.456	0.969		
Total obs. (households X waves)			8,013			
Obs. with lagged data			5,443			
Number of households			2,500			

Note: The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Statistics computed using sample weights.

Table A2
Fixed effects joint estimates in details.

	Plus interaction		Occupation F.E.	
	(1)	(2)	(3)	(4)
Variables	Husbands ($j = 1$)	Wives ($j = 2$)	Husbands ($j = 1$)	Wives ($j = 2$)
Job change of j	−0.154***	0.058	−0.149***	0.046
	(0.039)	(0.038)	(0.039)	(0.037)
Job change of $-j$	−0.008	−0.029	−0.004	−0.034
	(0.037)	(0.040)	(0.037)	(0.039)
Job change of j & $-j$	0.416***	0.011	0.425***	0.024
	(0.069)	(0.071)	(0.069)	(0.071)
Moved	0.084**	0.219***	0.089**	0.214***
	(0.037)	(0.038)	(0.037)	(0.038)
Demographics:				
Age	−0.030	−0.041	−0.022	−0.053**
	(0.027)	(0.027)	(0.027)	(0.027)
Age squared	0.020	0.043	0.012	0.054*
	(0.028)	(0.029)	(0.028)	(0.029)
j self-employed	0.212**	−0.455***	0.197*	−0.417***
	(0.107)	(0.105)	(0.108)	(0.106)
$-j$ self-employed	0.221**	0.288***	0.208**	0.357***
	(0.103)	(0.110)	(0.102)	(0.110)
Family size	−0.023	0.024	−0.018	0.026
	(0.035)	(0.037)	(0.035)	(0.036)
Number of children	−0.022	−0.008	−0.020	−0.006
	(0.039)	(0.040)	(0.039)	(0.040)
Age of youngest child	0.005	0.004	0.004	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
House type: house	−0.269***	−0.175**	−0.270***	−0.183***
	(0.067)	(0.068)	(0.066)	(0.068)
Number of rooms	0.013	0.034***	0.012	0.037***
	(0.011)	(0.011)	(0.011)	(0.011)
Home owned	0.230***	−0.026	0.235***	−0.035
	(0.065)	(0.067)	(0.065)	(0.066)
Family income	−0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of vehicles	0.066**	0.036	0.063**	0.038
	(0.030)	(0.031)	(0.030)	(0.030)
Change in n. vehicles	−0.036*	−0.041*	−0.032	−0.041*
	(0.020)	(0.021)	(0.020)	(0.021)
Constant	0.683	0.750	0.741	0.812
	(1.387)	(1.410)	(1.390)	(1.408)
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Occupation fixed effects	No	No	Yes	Yes
Observations	5,443	5,443	5,443	5,443
R-squared	0.352	0.332	0.356	0.341

Note: Robust standard errors clustered at the household level in parentheses. The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Estimates computed using sample weights. The dependent variable is the change in the log of commuting time, Δlog(commuting). *** significant at 1 %; ** significant at 5 %; * significant at 10 %.

Note: Robust standard errors clustered at the household level in parentheses. The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Estimates computed using sample weights. The dependent variable is the change in the log of commuting time, Δlog(commuting). *** significant at 1 %; ** significant at 5 %; * significant at 10 %.

Table A3
Job changes and the sign of wage shocks, additional coefficients.

Variables	(1) Husbands ($j = 1$)	(2) Wives ($j = 2$)
Job change of j | $\Delta\log(\text{wage}_j) > 0$	−0.162***	0.107**
	(0.047)	(0.044)
Job change of j | $\Delta\log(\text{wage}_j) < 0$	−0.145***	−0.001
	(0.047)	(0.047)
Job change of $-j$ | $\Delta\log(\text{wage}_{-j}) > 0$	−0.015	−0.024
	(0.043)	(0.048)
Job change of $-j$ | $\Delta\log(\text{wage}_{-j}) < 0$	0.001	−0.031
	(0.046)	(0.048)
Job change of j & $-j$	0.419***	0.004
	(0.069)	(0.071)
Moved	0.084**	0.217***
	(0.037)	(0.038)
Demographics		
Age	−0.030	−0.041
	(0.027)	(0.027)
Age squared	0.020	0.043
	(0.028)	(0.029)
j self-employed	0.211**	−0.433***
	(0.107)	(0.106)
$-j$ self-employed	0.218**	0.293***
	(0.103)	(0.110)
Family size	−0.022	0.022
	(0.035)	(0.037)
Number of children	−0.023	−0.007
	(0.039)	(0.040)
Age of youngest child	0.005	0.004
	(0.004)	(0.004)
House type: house	−0.269***	−0.170**
	(0.067)	(0.068)
Number of rooms	0.013	0.034***
	(0.011)	(0.011)
Home owned	0.230***	−0.028
	(0.065)	(0.067)
Family income	0.000	0.000
	(0.000)	(0.000)
Number of vehicles	0.065**	0.038
	(0.030)	(0.031)
Change in n. vehicles	−0.035*	−0.041**
	(0.020)	(0.021)
Constant	0.684	0.737
	(1.387)	(1.409)
Household fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	5,443	5,443
R-squared	0.352	0.333

Table A4
Heterogeneity, coefficient estimates.

	Age cohorts		Kids under 5 years	
	(1)	(2)	(3)	(4)
Variables	Husbands ($j = 1$)	Wives ($j = 2$)	Husbands ($j = 1$)	Wives ($j = 2$)
Job change of j	−0.356***	0.046	−0.167***	0.099**
	(0.066)	(0.077)	(0.043)	(0.042)
Job change of $j\times$ gen X	0.373***	0.056		
	(0.088)	(0.093)		
Job change of $j\times$ millenial	0.189*	−0.059		
	(0.104)	(0.104)		
Job change of $j\times$ kids under 5 years			0.048	−0.192**

(*continued on next page*)

Table A4 (*continued*)

Variables	Age cohorts (1) Husbands ($j = 1$)	(2) Wives ($j = 2$)	Kids under 5 years (3) Husbands ($j = 1$)	(4) Wives ($j = 2$)
			(0.084)	(0.085)
Job change of $-j$	0.084	−0.073	0.029	−0.020
	(0.069)	(0.069)	(0.041)	(0.044)
Job change of $-j\times$ gen X	−0.105	0.030		
	(0.085)	(0.094)		
Job change of $-j\times$ millenial	−0.140	0.093		
	(0.104)	(0.101)		
Job change of $-j\times$ kids under 5 years			−0.165**	−0.066
			(0.082)	(0.086)
Job change of j & $-j$	0.244	0.183	0.396***	0.082
	(0.177)	(0.169)	(0.081)	(0.083)
Job change of j & $-j\times$ gen X	0.106	−0.091		
	(0.204)	(0.202)		
Job change of j & $-j\times$ millenial	0.241	−0.285		
	(0.215)	(0.204)		
Job change of j & $-j\times$ kids under 5 years			0.097	−0.149
			(0.150)	(0.154)
Moved	0.113	0.098	0.086**	0.195***
	(0.088)	(0.093)	(0.043)	(0.044)
Moved × gen X	−0.032	0.163		
	(0.103)	(0.110)		
Moved × millenial	−0.032	0.138		
	(0.108)	(0.109)		
Moved × kids under 5 years			0.003	0.077
			(0.072)	(0.074)
Demographics				
Age	−0.029	−0.043	−0.030	−0.045*
	(0.027)	(0.027)	(0.027)	(0.027)
Age squared	0.019	0.046	0.021	0.048*
	(0.028)	(0.029)	(0.028)	(0.029)
j self-employed	0.184*	−0.460***	0.202*	−0.471***
	(0.107)	(0.105)	(0.107)	(0.105)
$-j$ self-employed	0.228**	0.289***	0.214**	0.300***
	(0.103)	(0.110)	(0.103)	(0.110)
Family size	−0.027	0.021	−0.023	0.027
	(0.035)	(0.037)	(0.035)	(0.037)
Number of children	−0.021	−0.004	−0.019	0.004
	(0.039)	(0.040)	(0.039)	(0.040)
Age of youngest child	0.005	0.003	0.005	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
House type: house	−0.264***	−0.177**	−0.270***	−0.179***
	(0.067)	(0.069)	(0.067)	(0.069)
Number of rooms	0.012	0.034***	0.014	0.034***
	(0.011)	(0.011)	(0.011)	(0.011)
Home owned	0.231***	−0.034	0.228***	−0.025
	(0.065)	(0.067)	(0.065)	(0.067)
Family income	−0.000	0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of vehicles	0.072**	0.037	0.068**	0.039
	(0.030)	(0.031)	(0.030)	(0.030)
Change in n. vehicles	−0.037*	−0.040*	−0.037*	−0.042**
	(0.020)	(0.021)	(0.020)	(0.021)
Constant	0.700	0.803	0.714	0.842
	(1.385)	(1.411)	(1.387)	(1.408)
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	5,443	5,443	5,443	5,443
R-squared	0.355	0.333	0.352	0.334

Note: Robust standard errors clustered at the household level in parentheses. The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Estimates computed using sample weights. The dependent variable is the change in the log of commuting time, Δlog(commuting). Reference for age cohorts: boomers (born before 1965). Gen X defined as those born between 1965 and 1980. Millenials defined as those born after 1980. *** significant at 1 %; ** significant at 5 %; * significant at 10 %.

Table A5
Robusntess checks, additional coefficients.

	Without "moved" control		Excluding movers	
	(1)	(2)	(3)	(5)
Variables	Husbands ($j = 1$)	Wives ($j = 2$)	Husbands ($j = 1$)	Husbands ($j = 1$)
Job change of j	−0.151***	0.055	−0.167***	0.062
	(0.039)	(0.038)	(0.044)	(0.040)
Job change of $-j$	−0.009	−0.023	0.009	−0.063
	(0.037)	(0.040)	(0.042)	(0.042)
Job change of j & $-j$	0.429***	0.044	0.324***	−0.045
	(0.069)	(0.071)	(0.091)	(0.087)
Moved	–	–	–	–
Demographics				
Age	−0.032	−0.049*	−0.019	−0.024
	(0.027)	(0.027)	(0.030)	(0.029)
Age squared	0.022	0.051*	0.013	0.024
	(0.028)	(0.029)	(0.031)	(0.030)
j self-employed	0.218**	−0.462***	0.177	−0.312***
	(0.107)	(0.106)	(0.130)	(0.111)
$-j$ self-employed	0.219**	0.302***	0.187	0.236*
	(0.103)	(0.110)	(0.115)	(0.125)
Family size	−0.022	0.026	−0.012	0.011
	(0.035)	(0.037)	(0.038)	(0.037)
Number of children	−0.025	−0.014	−0.008	−0.055
	(0.039)	(0.040)	(0.042)	(0.041)
Age of youngest child	0.005	0.003	0.003	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
House type: house	−0.259***	−0.149**	−0.359***	−0.118
	(0.066)	(0.068)	(0.093)	(0.089)
Number of rooms	0.013	0.034***	0.010	0.034***
	(0.011)	(0.011)	(0.013)	(0.012)
Home owned	0.221***	−0.048	0.278***	0.037
	(0.065)	(0.067)	(0.101)	(0.098)
Family income	0.000	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Number of vehicles	0.066**	0.037	0.105***	0.035
	(0.030)	(0.031)	(0.032)	(0.031)
Change in n. vehicles	−0.036*	−0.041*	−0.067***	−0.031
	(0.020)	(0.021)	(0.022)	(0.021)
Constant	0.822	1.153	0.346	0.268
	(1.387)	(1.413)	(0.754)	(0.692)
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	5,443	5,443	4,191	4,191
R-squared	0.351	0.328	0.375	0.404

Note: Robust standard errors clustered at the household level in parentheses. The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Estimates computed using sample weights. The dependent variable is the change in the log of commuting time, Δlog(commuting). *** significant at 1 %; ** significant at 5 %; * significant at 10 %.

Table A6
Non-short-term effects, additional coefficients.

	(1)	(2)	(3)	(4)
Variables	Husbands	($j = 1$)	Wives	($j = 2$)
Job change of j at date t	−0.233***	(0.057)	0.091*	(0.054)
Job change of j at date $t-1$	−0.014	(0.056)	0.018	(0.055)
Job change of $-j$ at date t	−0.028	(0.051)	−0.044	(0.060)
Job change of $-j$ at date $t-1$	0.016	(0.052)	0.042	(0.059)
Job change of j & $-j$ at date t	0.306***	(0.107)	−0.013	(0.113)
Job change of j & $-j$ at date $t-1$	−0.042	(0.104)	0.022	(0.110)
Moved at date t	0.043	(0.054)	0.104*	(0.057)
Moved at date $t-1$	−0.051	(0.054)	0.052	(0.057)
Demographics				
Age	0.089**	(0.045)	−0.063	(0.047)

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Table A6 (*continued*)

Variables	(1) Husbands	(2) ($j = 1$)	(3) Wives	(4) ($j = 2$)
Age squared	−0.112**	(0.046)	0.082*	(0.049)
j self-employed	0.607***	(0.199)	−0.428***	(0.150)
$-j$ self-employed	0.458***	(0.143)	0.716***	(0.210)
Family size	−0.121**	(0.049)	−0.104**	(0.052)
Number of children	−0.057	(0.055)	0.132**	(0.058)
Age of youngest child	0.005	(0.006)	0.002	(0.006)
House type: house	−0.197**	(0.094)	−0.163*	(0.099)
Number of rooms	0.004	(0.015)	0.013	(0.016)
Home owned	0.501***	(0.100)	−0.193*	(0.106)
Family income	−0.000	(0.000)	0.000	(0.000)
Number of vehicles	0.015	(0.043)	0.009	(0.045)
Change in n. vehicles	−0.013	(0.028)	−0.022	(0.029)
Constant	−3.679**	(1.596)	1.781	(1.629)
Household fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
Observations	2,904		2,904	
R-squared	0.384		0.373	

Note: Robust standard errors clustered at the household level in parentheses. The sample (PSID 2011–2019) is restricted to two-member stable households with positive labor supply in consecutive periods. Estimates computed using sample weights. The dependent variable is the change in the log of commuting time, Δlog(commuting). *** significant at 1 %; ** significant at 5 %; * significant at 10 %.

Data availability

Data will be made available on request.

References

Aguiar, M., Hurst, E., 2007. Measuring trends in leisure: the allocation of time over five decades. Q. J. Econ. 122 (3), 969–1006.

Akbari, S., Habib, K.N., 2018. Role of spatial configuration in commuting trade-offs of two-worker households: a case study in the greater Toronto area. Transp. Res. Rec. 2672 (3), 69–79.

Albert, J.F., Casado-Díaz, J.M., Simón, H., 2019. The commuting behaviour of self-employed workers: evidence for Spain. Pap. Reg. Sci. 98 (6), 2455–2477.

Alonso, W., 1964. Location and Landuse. Harvard University Press, Cambridge, Massachusetts.

Altonji, J.G., Smith Jr, A.A., Vidangos, I., 2013. Modeling earnings dynamics. Econometrica 81 (4), 1395–1454.

Arellano, M., Blundell, R., Bonhomme, S., 2018. Nonlinear persistence and partial insurance: income and consumption dynamics in the PSID. Am. Econ. Assoc.: Papers Proc. 108, 281–286.

Barrero, J.M., Bloom, N., Davis, S.J., 2023. The evolution of work from home. J. Econ. Perspect. 37 (4), 23–49.

Beige, S., Axhausen, K.W., 2017. The dynamics of commuting over the life course: swiss experiences. Transp. Res. A Policy Pract. 104, 179–194.

Blumenberg, E., King, H., 2019. Low-income workers, residential location, and the changing commute in the United States. Built Environ. 45 (4), 563–581.

Blundell, R., Pistaferri, L., Saporta-Eksten, I., 2016. Consumption inequality and family labor supply. Am. Econ. Rev. 106 (2), 387–435.

Bonke, J., 2005. Paid work and unpaid work: diary information versus questionnaire information. Soc. Indic. Res. 70, 349–368.

Brueckner, J.K., Thisse, J.F., Zenou, Y., 1999. Why is central Paris rich and downtown Detroit poor? An amenity-based theory. Eur. Econ. Rev. 43 (1), 91–107.

Carta, F., De Philippis, M., 2018. You've come a long way, baby. Husbands' commuting time and family labour supply. Reg. Sci. Urban Econ. 69, 25–37.

Ceder, A.A., Butcher, M., Wang, L., 2015. Optimization of bus stop placement for routes on uneven topography. Transp. Res. B Methodol. 74, 40–61.

Chiappori, P.A., 1992. Collective labor supply and welfare. J. Polit. Econ. 100 (3), 437–467.

Chiappori, P.A., Iyigun, M., Weiss, Y., 2009. Investment in schooling and the marriage market. Am. Econ. Rev. 99 (5), 1689–1713.

Chiappori, P.A., Dias, M.C., Meghir, C., 2020. Changes in assortative matching: Theory and evidence for the us. NBER Working Paper. w26932.

Christian, T.J., 2012. Automobile commuting duration and the quantity of time spent with spouse, children, and friends. Prev. Med. 55 (3), 215–218.

Clark, B., Chatterjee, K., Melia, S., 2016. Changes to commute mode: the role of life events, spatial context and environmental attitude. Transp. Res. A Policy Pract. 89, 89–105.

Clark, W.A., Huang, Y., Withers, S., 2003. Does commuting distance matter? Commuting tolerance and residential change. Reg. Sci. Urban Econ. 33 (2), 199–221.

Coria, J., Zhang, X.B., 2015. State-dependent enforcement to foster the adoption of new technologies. Environ. Resour. Econ. 62, 359–381.

Coria, J., Zhang, X.B., 2017. Optimal environmental road pricing and daily commuting patterns. Transp. Res. B Methodol. 105, 297–314.

Currie, G., Jain, T., Aston, L., 2021. Evidence of a post-COVID change in travel behaviour–self-reported expectations of commuting in Melbourne. Transp. Res. A Policy Pract. 153, 218–234.

Dargay, J.M., Clark, S., 2012. The determinants of long distance travel in Great Britain. Transp. Res. A Policy Pract. 46, 576–587.

Dickerson, A., Hole, A.R., Munford, L.A., 2014. The relationship between well-being and commuting revisited: does the choice of methodology matter? Reg. Sci. Urban Econ. 49, 321–329.

Farré, L., Jofre-Monseny, J., Torrecillas, J., 2023. Commuting time and the gender gap in labor market participation. J. Econ. Geogr. 23 (4), 847–870.

Flood, S. M., Sayer, L. C., Backman, D., & Chen, A. (2023). American Time Use Survey Data Extract Builder: Version 3.2 . College Park, MD: University of Maryland and Minneapolis, MN: IPUMS. https://doi.org/10.18128/D060.V3.2.

Frey, B.S., Stutzer, A., 2008. Stress that doesn't pay: the commuting paradox. Scand. J. Econ. 110 (2), 339–366.

Fu, S., Ross, S.L., 2013. Wage premia in employment clusters: how important is worker heterogeneity? J. Labor Econ. 31 (2), 271–304.

Fujiwara, D., Dolan, P., Lawton, R., Behzadnejad, F., Lagarde, A., Maxwell, C., & Peytrignet, S. (2020). Wellbeing costs of COVID-19 in the UK. Report to the World Health Organization.

Gerber, P., El-Geneidy, A., Manaugh, K., Lord, S., 2020. From workplace attachment to commuter satisfaction before and after a workplace relocation. Transport. Res. F: Traffic Psychol. Behav. 71, 168–181.
Ghasri, M., & Rashidi, T. H. (2019). Investigating the internal compromise between wife and husband's commute time changes in residential relocation. The Practice of Spatial Analysis: Essays in memory of Professor Pavlos Kanaroglou, 325-339.
Gimenez-Nadal, J.I., Molina, J.A., 2016. Commuting time and household responsibilities: evidence using propensity score matching. J. Reg. Sci. 56 (2), 332–359.
Gimenez-Nadal, J.I., Molina, J.A., Velilla, J., 2018a. The commuting behavior of workers in the United States: differences between the employed and the self-employed. J. Transp. Geogr. 66, 19–29.
Gimenez-Nadal, J.I., Molina, J.A., Velilla, J., 2018b. Spatial distribution of US employment in an urban efficiency wage setting. J. Reg. Sci. 58 (1), 141–158.
Giménez-Nadal, J.I., Molina, J.A., Velilla, J., 2021. Two-way commuting: asymmetries from time use surveys. J. Transp. Geogr. 95, 103146.
Giménez-Nadal, J.I., Molina, J.A., Velilla, J., 2022a. Trends in commuting time of European workers: a cross-country analysis. Transp. Policy 116, 327–342.
Gimenez-Nadal, J.I., Molina, J.A., Velilla, J., 2022b. Commuting time and sickness absence of US workers. Empirica 49 (3), 691–719.
Gobillon, L., Selod, H., Zenou, Y., 2007. The mechanisms of spatial mismatch. Urban Stud. 44 (12), 2401–2427.
Gottholmseder, G., Nowotny, K., Pruckner, G.J., Theurl, E., 2009. Stress perception and commuting. Health Econ. 18 (5), 559–576.
Green, A.E., 1997. A question of compromise? Case study evidence on the location and mobility strategies of dual career households. Reg. Stud. 31 (7), 641–657.
Grinza, E., Rycx, F., 2020. The impact of sickness absenteeism on firm productivity: new evidence from Belgian matched employer–employee panel data. Ind. Relat. 59 (1), 150–194.
Haque, M.B., Choudhury, C., Hess, S., dit Sourd, R.C., 2019. Modelling residential mobility decision and its impact on car ownership and travel mode. Travel Behav. Soc. 17, 104–119.
Hirte, G., Illmann, U., 2019. Household decision making on commuting and the commuting paradox. Empirica 46 (1), 63–101.
Hjorthol, R., Vagane, L., 2014. Allocation of tasks, arrangement of working hours and commuting in different Norwegian households. J. Transp. Geogr. 35, 75–83.
Hrehová, K., Sandow, E., Lindgren, U., 2023. Firm relocations, commuting and relationship stability. Reg. Stud. Reg. Sci. 10 (1), 194–217.
Huai, Y., Lo, H.K., Ng, K.F., 2021. Monocentric versus polycentric urban structure: case study in hong kong. Transp. Res. A Policy Pract. 151, 99–118.
Iwata, S., Tamada, K., 2014. The backward-bending commute times of married women with household responsibility. Transportation 41 (2), 251–278.
Jang, S., Yi, C., 2021. Imbalance between local commuting accessibility and residential locations of households by income class in the Seoul Metropolitan Area. Cities 109, 103011.
Kahneman, D., Krueger, A.B., 2006. Developments in the measurement of subjective well-being. J. Econ. Perspect. 20 (1), 3–24.
Kent, J.L., Mulley, C., Stevens, N., 2019. Transport and wellbeing in a newly constructed Greenfield estate: a quantitative exploration of the commuting experience. J. Transp. Health 13, 210–223.
Kim, K., Horner, M.W., 2021. Examining the impacts of the great recession on the commuting dynamics and jobs-housing balance of public and private sector workers. J. Transp. Geogr. 90, 102933.
Kim, S., 2020. Factors related to the commute time of dual-earner couples: from a family developmental perspective. Hum. Ecol. Res. 58 (2), 255–266.
Kimbrough, G., 2019. Measuring commuting in the american time use survey. J. Econ. Soc. Meas. 44 (1), 1–17.
Kirby, D.K., LeSage, J.P., 2009. Changes in commuting to work times over the 1990 to 2000 period. Reg. Sci. Urban Econ. 39 (4), 460–471.
Knox, P.L., McCarthy, L., 2005. Urbanization: An Introduction to Urban Geography, second ed. Prentice Hall, Englewood Cliffs, NJ.
Kohara, M., Sekijima, K., 2017. The effect of commuting time on married couples' time use. Econ. Anal. 195, 93–115.
Kunn-Nelen, A., 2016. Does commuting affect health? Health Econ. 25 (8), 984–1004.
Le Barbanchon, T., Rathelot, R., Roulet, A., 2021. Gender differences in job search: trading off commute against wage. Q. J. Econ. 136 (1), 381–426.
Lee, B.S., McDonald, J.F., 2003. Determinants of commuting time and distance for Seoul residents: the impact of family status on the commuting of women. Urban Stud. 40 (7), 1283–1302.
Leigh, J.P., 1986. Are compensating wages paid for time spent commuting? Appl. Econ. 18 (11), 1203–1214.
Liao, Y., Gil, J., Pereira, R.H., Yeh, S., Verendel, V., 2020. Disparities in travel times between car and transit: spatiotemporal patterns in cities. Sci. Rep. 10 (1), 4056.
Liotta, C., Viguié, V., Lepetit, Q., 2022. Testing the monocentric standard urban model in a global sample of cities. Reg. Sci. Urban Econ. 97, 103832.
Long, J., Szeto, W.Y., 2019. Congestion and environmental toll schemes for the morning commute with heterogeneous users and parallel routes. Transp. Res. B Methodol. 129, 305–333.
Lunke, E.B., Fearnley, N., Aarhaug, J., 2023. The geography of public transport competitiveness in thirteen medium sized cities. Environ. Plann. B: Urban Anal. City Sci. 50 (8), 2071–2086.
Ma, L., Huang, Y., Shi, W., Lin, J., 2025. Relocating home or changing job? The impact of long commuting. J. Transp. Geogr. 123, 104114.
Madden, J.F., 1981. Why women work closer to home. Urban Stud. 18 (2), 181–194.
Maheshwari, R., Van Acker, V., De Vos, J., Witlox, F., 2023. A multi-perspective review of the impact of a workplace relocation on commuting behaviour, commuting satisfaction and subjective well-being. Transp. Rev. 43 (3), 385–406.
Manning, A., 2003. The real thin theory: monopsony in modern labour markets. Labour Econ. 10 (2), 105–131.
McQuaid, R.W., Chen, T., 2012. Commuting times–the role of gender, children and part-time work. Res. Transp. Econ. 34 (1), 66–73.
Mills, E.S., 1967. An aggregative model of resource allocation in a metropolitan area. Am. Econ. Rev. 57 (2), 197–210.
Morris, E.A., Zhou, Y., 2018. Are long commutes short on benefits? Commute duration and various manifestations of well-being. Travel Behav. Soc. 11, 101–110.
Mulalic, I., Van Ommeren, J.N., Pilegaard, N., 2014. Wages and commuting: Quasi-natural experiments' evidence from firms that relocate. Econ. J. 124 (579), 1086–1105.
Muth, R., 1969. Cities and Housing: The Spatial Pattern of Urban Residential Land Use. University of Chicago Press, Chicago, IL.
Naess, P., Strand, A., Wolday, F., Stefansdottir, H., 2019. Residential location, commuting and non-work travel in two urban areas of different size and with different center structures. Prog. Plan. 128, 1–36.
Neto, R.S., Duarte, G., Páez, A., 2015. Gender and commuting time in São Paulo metropolitan region. Urban Stud. 52 (2), 298–313.
Oakil, A.T.M., Nijland, L., Dijst, M., 2016. Rush hour commuting in the Netherlands: gender-specific household activities and personal attitudes towards responsibility sharing. Travel Behav. Soc. 4, 79–87.
Oreffice, S., Sansone, D., 2023. Commuting to work and gender norms by sexual orientation. Labour Econ. forthcoming.
Picard, N., Dantan, S., De Palma, A., 2018. Mobility decisions within couples. Theor. Decis. 84 (2), 149–180.
Prillwitz, J., Harms, S., Lanzendorf, M., 2007. Interactions between residential relocations, life course events, and daily commute distances. Transp. Res. Rec. 2021 (1), 64–69.
Pritchard, R., Frøyen, Y., 2019. Location, location, relocation: how the relocation of offices from suburbs to the inner city impacts commuting on foot and by bike. Eur. Transp. Res. Rev. 11, 1–20.
PSID (2019). Panel Study of Income Dynamics, public use dataset. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI (2019).
PSID (2021). Main Interview User Manual: Release 2021. Institute for Social Research, University of Michigan, March, 2021.
Rau, H., Popp, M., Namberger, P., Mögele, M., 2019. Short distance, big impact: the effects of intra-city workplace relocation on staff mobility practices. J. Transp. Geogr. 79, 102483.
Roberts, J., Hodgson, R., Dolan, P., 2011. "It's driving her mad": gender differences in the effects of commuting on psychological health. J. Health Econ. 30 (5), 1064–1076.
Ross, S.L., Zenou, Y., 2008. Are shirking and leisure substitutable? An empirical test of efficiency wages based on urban economic theory. Reg. Sci. Urban Econ. 38 (5), 498–517.
Rouwendal, J., Rietveld, P., 1994. Changes in commuting distances of Dutch households. Urban Stud. 31 (9), 1545–1557.
Rouwendal, J., van der Vlist, A., 2005. A dynamic model of commutes. Environ Plan A 37 (12), 2209–2232.

Ruiz, M.C., Devonport, T.J., Chen-Wilson, C.H.J., Nicholls, W., Cagas, J.Y., Fernandez-Montalvo, J., Robazza, C., 2021. A cross-cultural exploratory study of health behaviors and well-being during COVID-19. Front. Psychol. 11, 3897.
Ruppert, P., Stancanelli, E., Wasmer, E., 2009. Commuting, wages and bargaining power. Ann. Econ. Stat. 95 (96), 201–220.
Sandow, E., Westin, K., 2010. The persevering commuter–duration of long-distance commuting. Transp. Res. A Policy Pract. 44 (6), 433–445.
Scheiner, J., 2010. Social inequalities in travel behaviour: trip distances in the context of residential self-selection and lifestyles. J. Transp. Geogr. 18 (6), 679–690.
Scheiner, J., 2016. Time use and the life course: a study of key events in the lives of men and women using panel data. Eur. J. Transp. Infrastruct. Res. 16 (4).
Schoenduwe, R., Mueller, M.G., Peters, A., Lanzendorf, M., 2015. Analysing mobility biographies with the life course calendar: a retrospective survey methodology for longitudinal data collection. J. Transp. Geogr. 42, 98–109.
Simonsohn, U., 2006. New Yorkers commute more everywhere: contrast effects in the field. Rev. Econ. Stat. 88 (1), 1–9.
Smart, M.J., Klein, N.J., 2020. Disentangling the role of cars and transit in employment and labor earnings. Transportation 47 (3), 1275–1309.
Sprumont, F., Viti, F., Caruso, G., König, A., 2014. Workplace relocation and mobility changes in a transnational metropolitan area: the case of the University of Luxembourg. Transp. Res. Procedia 4, 286–299.
Stenpaß, A., Kley, S., 2020. It's getting late today, please do the laundry: the influence of long-distance commuting on the division of domestic labor. J. Fam. Res. 32 (2), 274–306.
Stone, A.A., Schneider, S., 2016. Commuting episodes in the United States: their correlates with experiential wellbeing from the American Time Use Survey. Transport. Res. F: Traffic Psychol. Behav. 42, 117–124.
Swardh, J.E., Algers, S., 2016. Willingness to accept commuting time within the household: stated preference evidence. Transportation 43, 219–241.
Ta, N., Wang, X., Hu, L., Liu, Z., 2022. Gender difference in commuting travel: a comparative study of suburban residents in Beijing and Shanghai. Travel Behav. Soc. 28, 196–203.
Tao, Y., Petrović, A., van Ham, M., Fu, X., 2023a. Residential relocation as a key event in commuting mode shift. Transp. Res. Part D: Transp. Environ. 119, 103772.
Tao, Y., van Ham, M., Petrović, A., Ta, N., 2023b. A household perspective on the commuting paradox: Longitudinal relationships between commuting time and subjective wellbeing for couples in China. Transp. Res. A Policy Pract. 170, 103640.
Theloudis, A., 2021. Consumption inequality across heterogeneous families. Eur. Econ. Rev. 136, 103765.
Thomas, F.M., Charlton, S.G., Lewis, I., Nandavar, S., 2021. Commuting before and after COVID-19. Transp. Res. Interdiscip. Perspect. 11, 100423.
Van Acker, V., Witlox, F., 2011. Commuting trips within tours: how is commuting related to land use? Transportation 38 (3), 465–486.
Van Ommeren, J.N., Gutiérrez-i-Puigarnau, E., 2011. Are workers with a long commute less productive? An empirical analysis of absenteeism. Reg. Sci. Urban Econ. 41 (1), 1–8.
Van Ommeren, J., Rietveld, P., Nijkamp, P., 1997. Commuting: in search of jobs and residences. J. Urban Econ. 42 (3), 402–421.
Van Ommeren, J.N., Rietveld, P., Nijkamp, P., 1998. Spatial moving behaviour of two-earner households. J. Reg. Sci. 38 (1), 23–41.
Van Ommeren, J., Rietveld, P., Nijkamp, P., 1999. Job moving, residential moving, and commuting: a search perspective. J. Urban Econ. 46 (2), 230–253.
Van Ommeren, J.N., van der Straaten, J.W., 2008. The effect of search imperfections on commuting behaviour: evidence from employed and self-employed workers. Reg. Sci. Urban Econ. 38 (2), 127–147.
Von Behren, S., Puhe, M., Chlond, B., 2018. Office relocation and changes in travel behavior: capturing the effects including the adaptation phase. Transp. Res. Procedia 32, 573–584.
Vosough, S., Poorzahedy, H., Lindsey, R., 2020. Predictive cordon pricing to reduce air pollution. Transp. Res. Part D: Transp. Environ. 88, 102564.
Wener, R.E., Evans, G.W., Phillips, D., Nadler, N., 2003. Running for the 7:45: the effects of public transit improvements on commuter stress. Transportation 30, 203–220.
White, M.J., 1986. Sex differences in urban commuting patterns. Am. Econ. Rev. 76 (2), 368–372.
Wong, S., McLafferty, S.L., Planey, A.M., Preston, V.A., 2020. Disability, wages, and commuting in New York. J. Transp. Geogr. 87, 102818.
Xue, F., Yao, E., Jin, F., 2020. Exploring residential relocation behavior for families with workers and students; a study from Beijing, China. J. Transp. Geography 89, 102893.
Yang, X., Day, J.E., Langford, B.C., Cherry, C.R., Jones, L.R., Han, S.S., Sun, J., 2017. Commute responses to employment decentralization: anticipated versus actual mode choice behaviors of new town employees in Kunming, China. Transp. Res. Part D: Transp. Environ. 52, 454–470.
Yee-Kan, M., 2008. Measuring housework participation: the gap between "stylised" questionnaire estimates and diary-based estimates. Soc. Indic. Res. 86 (3), 381–400.
Zarabi, Z., Manaugh, K., Lord, S., 2019. The impacts of residential relocation on commute habits: a qualitative perspective on households' mobility behaviors and strategies. Travel Behav. Soc. 16, 131–142.
Zellner, A., 1962. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. J. Am. Stat. Assoc. 57 (298), 348–368.
Zhao, P., Zhang, Y., 2018. Travel behaviour and life course: Examining changes in car use after residential relocation in Beijing. J. Transp. Geogr. 73, 41–53.