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DISCUSSION PAPER SERIES

IZA DP No. 18232

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ABSTRACT

Will You Follow Your Job to the Suburbs? Commuting, Locational Amenities and Wages in a Large Metro Area

We examine how relocations from the center to the suburbs of establishments employing mainly skilled workers affect the composition and wages of their employees. Using data from the Paris metro area, we find that these relocations increase average commuting time by 19%. In response, firms compensate highly paid workers with 10 to 20% of their hourly wage per additional hour of commuting. Lower-paid workers receive no compensation and are more likely to leave. Consistent with workers valuing locational amenities, we find little increase in separation and no wage adjustment for increased commuting time when establishments relocate to more attractive neighborhoods.

JEL Classification: J16, D13, J18

Keywords: labor supply, commuting time, firm's location

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Introduction

One of a firm's most important decisions is choosing its establishments' locations. A large literature in urban economics highlights that firms locate in large metro areas despite their higher rents because agglomeration economies increase their productivity (Combes and Gobillon, 2015). Being in a large agglomeration might, in particular, improve both the quantity and quality of matches between workers and firms (Duranton and Puga, 2004, 2020). As suggested by standard urban economics models (see Zenou, 2009, for an overview), similar considerations may influence firms' location choices *within* metro areas. In the largest metro areas such as New York, London, or Paris, establishments located in the expensive but well-connected center should be particularly attractive as they can offer short commuting times via public transportation, along with numerous leisure opportunities near the establishment (Carlino and Saiz, 2019).

In recent decades, however, in response to a dramatic increase in rental costs in city centers, the share of jobs in the suburbs has grown rapidly and many large establishments have relocated to the suburbs (Hill and Brennan, 2005; Glaeser et al., 2001). In the Paris metro area considered here, among other notable examples, the car manufacturer Peugeot (PSA) relocated more than 1 200 employees in 2019 from the prestigious 16$^{\text{th}}$ Arrondissement in central Paris to Poissy, a working-class suburb located 24 km from the city center (Livois, 2017). Similarly, in 2014, BNP Paribas, a French bank, relocated 3 000 employees from the Opéra district in central Paris to Pantin, in the poorer northern inner suburbs (Reibaud, 2010). Similar patterns are also observed in other large metro areas such as London and New York.[1]

Establishment relocations are particularly interesting to study in order to understand the costs and benefits for employers associated with locating an establishment in different parts of the metro area. By relocating an establishment where rents are cheaper, firms can rent more space at a lower cost. However, attracting or retaining workers after relocating to a more remote and less prestigious location might be difficult. If incumbent workers hired before the relocation are costly to substitute and thus benefit from rents associated with the employment relationship, firms relocating to the suburbs might need to increase their wages to retain them. In contrast, if

[1] For example, in London, the bank HSBC relocated more than 4 000 employees in 2002 from central London to Canary Wharf, about 6 miles away (Megaw, 2023). In New York, in 2001, Conde Nast, a press publisher, partly relocated its offices from Manhattan to New Jersey (Wong, 2021).

incumbent workers can be easily replaced, workers with longer commutes will be replaced by workers living in the suburbs close to the establishment, who thus should accept lower wages.

Despite the importance of these questions, credible evidence on how relocating an establishment within a metro area affects wages and employee composition remains scarce. One empirical challenge is that the data requirements to study these questions are considerable. In addition to the fact that relocations are rare events, detailed information on the establishment's location and workers' place of residence is required to identify their consequences. To fulfill these requirements, we use exhaustive and rich employer-employee longitudinal administrative data within the Paris metro area in France that contains such information over 15 years.

The Paris metro area provides an ideal setting to study these questions. With more than 12 million inhabitants and 6 million workers, it is the largest metro area in Europe after London and accounts for 23% of French employment. Because of its large size and our access to exhaustive administrative data, we follow the relocation of about 2 800 establishments with more than 20 employees observed between 2003 and 2018, for which more than 50% of the original employees remain in the establishment after the relocation. Among these relocations, 19% involve a relocation from the center to the suburbs, but 9% instead occur from the suburbs to the center of the metro area.

We find that establishments in our sample relocate relatively far, on average about 5 km (3.1 mi) from their initial location, with relocations from the center to the suburbs increasing average commuting time by public transportation by 19% (10 minutes) and by more than 60% (30 minutes) for one tenth of workers. To understand their consequences, we investigate how changes in commuting times associated with a relocation affect incumbent workers' job separation and wages. Our identification assumption, for which we find strong support in the data, is that differences in commuting time changes across workers, induced by the relocation, are not systematically correlated with preexisting wage trends or risks of job separation. Consequently, these differences allow us to assess how higher or lower commuting times driven by the relocation affect job separation and wages, and whether these effects depend on the establishment relocating to a neighborhood with better or worse amenities.

Consistent with the hypothesis that workers dislike commuting, we find a one-hour increase in commuting time (about two standard deviations) raises their probability of leaving the firm

by 2.1 p.p. in the relocation year, with effects persisting up to three years after the relocation. As predicted by a simple rent-sharing model, firms also increase the wages of workers who remain in the establishment but for whom commuting time has increased due to the relocation, with baseline estimates indicating a small but statistically significant 1.1% increase in log hourly wages for each additional hour of commuting. However, wages are adjusted asymmetrically, as we find no evidence that firms cut wages of workers who benefit from a shorter commute. Whether workers are compensated also varies dramatically with their occupation: we find little evidence of wage adjustment for workers in low- and medium-paid occupations, who, as a result, are also more likely to leave the establishment. For workers in highly paid occupations, the wage increases are larger by a third relative to the baseline and strongly statistically significant.

We also find strong evidence that the consequences of relocations depend on how they change the locational amenities surrounding the establishment. For relocations from the center to the suburbs, which tend to be associated with a downgrade in locational amenities, we find that longer commuting times are associated with increases in wages that are twice as large as the baseline estimates. In contrast, for relocations from the suburbs to the center, in which locational amenities are likely to improve, we find no evidence that firms compensate workers for increased commuting time. Importantly, commuting time increases also have no statistically significant effects on the risk of separation in these cases, suggesting that workers might be willing to accept a longer commute for the benefits of working in a more desirable neighborhood.

Overall, our findings contrast with the predictions of competitive urban economics models in which firms always hire workers living closer to the establishments (Fujita et al., 1997). Our findings that firms only differentially compensate highly paid workers are consistent with models of the labor market with frictions, in which workers more costly to recruit benefit from rents and possess stronger bargaining power. However, even if our results should be interpreted with caution, since they may be attenuated by measurement errors in commuting time, our estimates indicate that even highly paid workers are far from being fully compensated as an additional hour of commuting is only compensated by 10 to 20% of their hourly wage. The effects of longer commuting time on job separation are also moderate as a one standard deviation increase in commuting time, about 30 minutes one-way, and thus 1 hour per day, is associated with only a 2.6 percentage points increase in the separation rate after three years. The fact that

many workers remain in the establishment despite substantially longer commutes after the relocation and little or no wage compensation suggests that employers possess considerable power to unilaterally affect working conditions, even in a large metro area with a high concentration of alternative employers.

Related literature— We contribute to several strands of the literature. Our work is first related to the literature on the determinants of firms' location choice. Most of this literature has focused on the location choice across regions or commuting zones, emphasizing the importance of agglomeration economies (Alcácer and Chung, 2007; Ellison et al., 2010), differences in local tax rates (Devereux and Griffith, 1998), or government subsidies (Devereux et al., 2007). In contrast to this literature, we investigate the consequences of the location choice *within* metro areas and document their consequences on employees' commuting time and wages. By using relocations and thus following the same establishments and workers over time, our estimates are unaffected by systematic differences between establishments and workers across different parts of the metro area.

Our work is also related to the literature linking commuting time to labor supply and wages, which includes Zax (1991), Gronberg and Reed (1994), Calfee and Winston (1998), Van Ommeren et al. (2000), and more recently Manning and Petrongolo (2017) and Le Barbanchon et al. (2021), who studied how commuting time to a potential job affects the labor supply of unemployed workers. As the earlier literature used cross-sectional data, omitted variable biases might affect these early results, as suggested by panel data estimates using voluntary changes of employer reported by Manning (2003). However, relying on voluntary changes might also be problematic, as such moves might be driven by unobserved worker-level shocks. By contrast, we exploit changes in commuting time from establishment relocations, which are more likely to be uncorrelated with worker-specific shocks. In addition, as we use differences across workers initially in the same establishment, we control for the effects of time-varying establishment-specific shocks affecting all workers in the same establishment similarly.

Our empirical approach extends Zax and Kain (1991, 1996), who studied how the relocation of the headquarters of a large firm in the service industry in Detroit in the 1970s from the center to the suburbs affected the share of workers from different parts of the metro area. Our approach is also similar to Mulalic et al. (2014), who provided one of the first quasi-experimental esti-

mates of compensating wage differentials for commuting time using administrative data from Denmark between 2003-7. However, our work differs in several important ways. First, unlike Mulalic et al. (2014), who consider relocations across all of Denmark, including urban and rural regions, we concentrate instead on a dense metro area, where the majority of workers are employed in highly paid occupations and might thus have higher bargaining power. Another important difference is that our sample is 30 times larger, as the Paris metro area has twice the population of Denmark, and covers over 13 years, compared to four years in their study. Such a large sample allows us to capture crucial differences across workers, as well as differences related to whether the relocation improves or downgrades locational amenities. Finally, we also explore the consequences of relocations not only on wages but also on the probability of quitting the establishment, following Zax and Kain (1991, 1996).

1 Conceptual framework

The relocation of an establishment might dramatically affect crucial non-wage job characteristics, which are valued by workers such as commuting time to work or the quality of locational amenities in the neighborhood (Rosen, 1986). However, as discussed by Mulalic et al. (2014), whether firms compensate their employees for a change in these working conditions due to a relocation depends on whether labor markets are assumed to be competitive. In frictionless urban economic models with workers homogeneous in preferences and productivity, workers can be easily replaced (Fujita, 1989). These models thus predict that, after a relocation to a secondary economic center, workers who live too far from the new location will be replaced by workers living closer to the establishment (Fujita et al., 1997). In this setting, wages do not depend on commuting time as lower housing costs compensate for the longer commutes of workers living far from economic centers.

These predictions contrast with those of noncompetitive models with frictions, in which workers and firms search for each other, resulting in match-specific rents. Standard matching models typically assume that, once matched, employers and workers bargain over wages (Pissarides, 2000). When workers' utility also depends on non-wage amenities, changes in these

amenities will affect wages.[2]

A simple illustrative model— To clarify the empirical implications of the noncompetitive setting, we sketch a stylized model in which wages are determined through Nash bargaining between the worker and the firm. The model consists of two periods: in the first, the firm and the worker meet and bargain over wages; in the second, an unanticipated relocation of the establishment occurs. At this point, the firm and the worker decide whether to maintain the employment relationship and rebargain wages accordingly or to terminate it. To keep the analysis as simple as possible, workers are assumed to live hand-to-mouth and consume all their income in each period. Consistent with the empirical evidence presented below, we also assume high mobility costs such that workers' residential location remains fixed in the second period and does not adjust in response to the establishment relocation.

Following Manning (2003), the instantaneous (indirect) utility of worker i in each period is linear in wages w_i and commuting time τ_i. Workers' utility also depends on the level of locational amenities in the neighborhood, denoted by a, which is measured in the same units as wages. The utility function is thus specified as $U(w_i, \tau_i, a) = w_i - c\tau_i + a$ where c represents the unit cost of commuting.[3] Workers stay in the establishment if their utility is superior to their reservation utility denoted b.

For firms, the profit of a match is given by $J = y_i - w_i$ where y_i is the worker's output. After having met, assuming that the match is profitable, wages are determined according to the Nash solution to a bargaining problem with bargaining power η such that wages are given by $w_i = \eta y_i + (1-\eta)(c\tau_i - a + b)$. The maximum commuting time for the match to be profitable is given by $\tilde{\tau}_i = (y_i + a - b)/c$, which is increasing in amenities a and decreasing in outside opportunities b.

[2]Other non-competitive models relying on alternative assumptions for wage formation also predict that wages will be correlated with workers' commuting time. Wage-posting models, in which firms post wages prior to meeting workers, predict that wages will be positively correlated with workers' commuting distance, as greater commuting distance increases workers' reservation wage (Manning, 2003). A similar prediction is borne out in efficiency wage models, where workers' efforts are imperfectly observable. In these models, firms pay higher wages to workers with longer commutes to provide them with incentives to make efforts (Ross and Zenou, 2008; Van Ommeren and Gutiérrez-i Puigarnau, 2011).

[3]While standard (see, e.g. Van den Berg and Gorter, 1997; Ruppert et al., 2009), an unrealistic consequence of the additivity and linearity of the utility function is that the marginal disutility of commuting time is constant and does not depend on the wage level. In practice, changes in wages, or household income more generally, might affect commuting behavior by increasing the opportunity cost of travel time or by allowing workers to live closer to their workplace (Gutiérrez-i Puigarnau et al., 2016). Similarly, the valuations of amenities in the neighborhood of the establishment might depend on the wage and might differ between low-paid and highly paid workers.

In the second period, the relocation of the establishment changes commuting time by $\Delta\tau_i = \tau_i' - \tau_i$, where τ_i' denotes the new commuting time, which can be either longer or shorter than before. The relocation also changes neighborhood amenities, with the change given by $\Delta a = a' - a$, which is positive if the new location offers better amenities, and negative otherwise. Additionally, we assume that $\eta\Delta y_i = \varepsilon_i$, where ε_i represents a random, idiosyncratic change in the worker's productivity, normalized to have an average of zero and assumed to be uncorrelated with $\Delta\tau_i$.[4]

Assuming the new commuting time is such that $\tau_i' < \tilde{\tau}_i$, which implies the match remains profitable, and that the worker and the firm renegotiate wages after the relocation, then the change in wage following the relocation is given by:

$$\Delta w_i = -(1-\eta)\Delta a + (1-\eta)c\Delta\tau_i + \varepsilon_i \tag{1}$$

The previous equation implies that the parameter $(1-\eta)c$, which determines the effect of commuting time on wages, can be estimated with a linear regression of changes in wages on individual changes in commuting time. The econometric model should include establishment fixed effects to capture the consequences of changes in amenities $-(1-\eta)\Delta a$, which affect the wages of all workers at the establishment similarly.[5]

Two important assumptions are required to identify the parameter $(1-\eta)c$ in Eq. 1: first, unobserved workers' productivity changes Δy_i should not be correlated with longer commuting time. If longer commutes decrease workers' productivity as suggested by Van Ommeren and Gutiérrez-i Puigarnau (2011), our estimates are downward biased as commuting time changes are negatively correlated with unobserved changes in workers' productivity contained in the error term.

A second important assumption is that any change in commuting time or amenities affects wages, whether the change is positive or negative. Net of the effects of amenities, this assumption implies that while the wages of workers facing an increase in commuting time should

[4] Alternatively, we could assume that Δy_i could be decomposed into a change in productivity that affects all workers in the establishment similarly, which would be accounted for empirically by the inclusion of establishment fixed effects in the econometric model, and an idiosyncratic worker specific component uncorrelated with the increase in commuting time.

[5] In practice, following most of the literature (Card et al., 2014), we will consider below a log-linear approximation of the previous equation, using changes in log wages as the dependent variable.

increase on average, the wages of workers benefiting from a *decrease* in commuting time should symmetrically decrease. In practice, however, a large literature has documented workers' aversion to nominal wage cuts (Altonji and Devereux, 2000; Kahneman et al., 1986). In addition, while the flexible component of wages can be adjusted, and wages in France can be quite flexible as a result (Verdugo, 2016), base wages specified in the labor contract are more rigid as they cannot be renegotiated without the worker's consent. If renegotiations occur by mutual consent (Malcomson, 1997) and workers are only paid their base wages, employees may not accept wage cuts justified by a relocation of their establishment closer to their home.

If wage adjustments are asymmetric, as suggested by the empirical evidence presented below, then the correlation between wage changes and commuting time changes depends on the sign of the changes in amenities, which determines the share of workers that needs to be compensated. As shown in Appendix A.1, the estimated coefficient from the regression of wage changes on commuting time changes will be attenuated when Δa is positive and large, as improved amenities compensate for the utility loss from increases in commuting time.

Reallocation and job separation— Even if the surplus from the match remains positive, firms might prefer to search for a new worker instead of renegotiating wages after the relocation. As shown in Appendix A.1, firms will search for another worker when they anticipate that she will have a shorter commuting time, and thus accept a lower wage that offsets the costs of replacement. When firms can easily find similarly productive workers near the new location, the relocation will have a strong effect on job separation but little impact on wages, as predicted by competitive models.

Empirical implications — While simple, this theoretical framework offers several empirically testable hypotheses for analyzing how relocations affect the wages of incumbent workers. First, for workers who remain in the establishment after the relocation, if wages are bargained as a function of non-wage amenities such as commuting time, then firms should adjust wages to individual changes in commuting time resulting from the relocation. However, if the adjustment is asymmetric, meaning firms do not decrease wages, and locational amenities influence workers' utility, then changes in these amenities will affect the empirical correlation between wages and commuting times. As a result, we should observe a stronger effect of increases in

commuting time on wages when locational amenities deteriorate, such as in relocations from the center to remote suburbs.

A second important implication is that wage adjustments depend on the importance of frictions in the labor market, specifically, how easily incumbent workers with long commutes can be replaced and, for workers, how easily they can find alternative jobs offering higher utility. When there are few frictions, relocations will have a strong effect on job separation but little effect on wages. We assess the empirical relevance of these hypotheses in the rest of the paper.

2 Data and context

To examine the consequences of relocations, we combine employer-employee longitudinal administrative data that contain rich information on establishments and workers with publicly available commuting time data.

Longitudinal Employer-employee data — We use administrative data at the worker level for each French establishment in the Paris metro area from the DADS (*Déclaration administrative des données sociales*) over the period 2003-2018. The DADS is based on mandatory annual reports that employers have to submit for each of their employees.[6] We exploit the wage earner files (*DADS salariés*) that report information about the main job held by the worker in a given year. As a result, our sample includes only those workers for whom the establishment was their main employer throughout the year. The data report information on annual earnings, the number of hours and days worked, the industry code, and occupation. We use hourly wages as our primary measure of earnings, calculated by dividing total yearly earnings by the annual number of hours.[7] Since no information on education is reported, we approximate workers' skill levels using their occupations to distinguish between low-, medium- and highly paid occupations.[8] A limitation is that the data only report information on employees who have worked at least one day during the year and we have no information on workers who remain unemployed or exit the

[6]We accessed these data through the French Secure Data Access Center (CASD). We do not use data from before 2002 as they do not contain information that allows us to track workers over time.

[7]In the supplementary appendix S1, in accordance with recent evidence from Lachowska et al. (2022) for the US, we provide evidence corroborating the quality of the hours' information.

[8]Highly paid occupations include managers and high-level professionals, medium-paid occupations include technicians and associate professionals, and low-paid occupations include blue-collar workers. See Data Appendix A.2 for details.

labor force for more than one year.

The data contain distinct administrative identifiers for each firm and each of its establishments. While the original files do not contain an identifier that allows workers to be matched across yearly files, workers can be easily matched across years using retrospective information from the previous year contained in yearly files.[9] As detailed in the data Appendix A.2, using programs from Babet et al. (2025), we assign a consistent identifier over time to 98% of the workers in our sample.

Sample selection — We focus on standard employment relationships, excluding subsidized contracts for young workers, interns, and apprenticeships (4% of observations). For establishments, we only include those with more than 20 employees to ensure sufficient variation in commuting time across workers following the relocation. We focus on establishments in the manufacturing sector and in business services and exclude those specialized in local consumer services, thereby excluding bars, restaurants, and shops, and more generally establishments from the Hospitality, Wholesale and Retail Trade sectors. Overall, such establishments account for 50% of private sector employment in the metro area and up to 65% in the center.

Geographical definitions— In line with the organization of the local transportation networks, the Paris metro area, displayed in Panel A of Figure 1, is delineated by the boundaries of the Île-de-France region. As illustrated in the figure, the center of the metro area is defined using the municipality of Paris. Consistent with current common practice, the inner suburbs ('*petite couronne*' in French) are defined using the three most densely populated counties ('*departments*') bordering the municipality of Paris, while the outer suburbs ('*grande couronne*') include the remaining counties on the periphery of the metro area.

Our sample includes all workers living and employed in the metro area, thus including those in both the inner and outer suburbs. However, to study relocations, we restrict our sample to establishments relocating within the center and the *inner* suburbs, which account for over 90% of the relocations we identified in the data. Therefore, unless indicated otherwise, throughout the rest of the paper, the term relocations to the 'suburbs' refers to relocations into the inner

[9]The original data did not include any worker identifiers to preserve confidentiality. However, this constraint has recently been relaxed, and the French Statistical Institute has authorized researchers to match workers across yearly files using the procedure developed by Babet et al. (2025).

suburbs. One advantage of focusing on relocations within the center and inner suburbs is that they generate fewer measurement errors regarding their consequences on workers' commuting time. As most employers do not typically provide parking spaces in these zones, public transportation is, for most workers, not only the most efficient but also the only feasible commuting mode. Using the 2018 French census, we estimate that more than 78% of employees in these zones commute to work via public transportation, compared to 40% for employees in the outer suburbs (see also Acs and Laurent, 2021).

A second advantage of focusing on relocations within the center and the inner suburbs is that they have little effect on public transportation fares, thus affecting commuting time while leaving commuting costs broadly unchanged. We estimate that relocations change the fare zones for only 10% of workers in our sample, increasing the price of a monthly travelcard by a maximum of 20 euros during our sample period.[10]

Despite such a small additional cost, changes in fare zones could nevertheless affect our estimates, as French labor laws require employers to reimburse 50% of the cost of a travelcard subscription directly through the employee's wage bill, and we cannot identify this component of earnings from the data. To account for any systematic effects of changes in fare zones on wages, we include in our empirical specification presented below separate fixed effects for every combination of changes in fare zones.

Legal context of relocations— French labor laws permit employers to relocate an establishment and thus change the workplace of their employees without justification, provided the new location remains within the same 'geographical sector' (Maillard-Pinon, 2021). Within the Paris metro area, labor courts have always ruled that the center, inner suburbs, and outer suburbs are part of the same geographical sector. Employers have no legal obligation to compensate employees for the consequences of a relocation, except, as mentioned earlier, for the reimbursement of half of the additional cost resulting from a fare zone change for public transportation. Employees who do not accept the relocation can be dismissed without severance pay or compensation, regardless of their personal circumstances.

Because of legal constraints, work from home was also not a potential margin of adjust-

[10] As detailed in Appendix A.4, the reason is that the center (zone 1) and the nearby inner suburbs (zone 2) are always bundled together in travelcard subscriptions. In addition, after September 2015, fare zones were abolished for travelcard subscriptions, allowing travel across the entire metro area.

ment to relocations over the period we consider. As discussed by Goux and Maurin (2025), work from home was virtually nonexistent in France before 2017 as it required modifying each employee's labor contract to specify the conditions on a case-by-case basis. In 2017, a new law allowed firms to sign collective agreements on work from home, with the first agreements signed in 2018, which fall outside our study period.

Identifying relocations— Each establishment identifier corresponds to a unique address and a new identifier is issued when an establishment relocates to a different address, which allows us to easily identify relocations in our sample. We identify relocation events when at least 50% of workers observed in an establishment in year $t-1$ are employed in year t at a new establishment of the same firm but located in a different municipality or a different arrondissement within the municipality of Paris. As shown in the robustness section, our results are not sensitive to this 50% threshold. To test for potential anticipation, we restrict our sample to establishments and workers observed in the same establishment at least three years before the relocation. We also focus on establishments observed for at least three years after the relocation to capture medium-run wage responses. Given that our sample spans from 2003 to 2018, these restrictions imply that we focus on relocations occurring between 2006 and 2016. Importantly, our sample contains all identified relocations, regardless of their effect on the average commuting time of their workers, both those that increase average commuting time and those that decrease it.

An important question for interpreting our results is how different establishments that relocate are relative to others in the metro area. To answer this, Table 1 compares the main average characteristics of employees between relocating establishments and others from the same sectors. While establishments that relocate tend to have a lower median number of employees, other characteristics such as the average age, share of women, and sector distribution are very similar. The geographical distribution of employees' residences is also very similar between the two groups. However, even if the share of workers in highly paid occupations is substantially higher than the national average of 22% for France in both groups, establishments that relocate tend to employ a larger share of these workers, with a 8 p.p. difference relative to others. These differences in worker composition translate into median hourly wages that are 30% larger in relocating establishments.

To assess whether there are important differences among establishments that relocate, Ta-

ble 2 provides separate figures depending on whether their relocations are associated with substantial changes in locational amenities. To identify such relocations, we first distinguish relocations between the center and suburbs, which are likely to be associated with dramatic changes in commuting time and locational amenities. Since the center and the suburbs are quite heterogeneous, we also isolate relocations associated with a decline or increase in the housing price rank of the municipality by more than one quartile (see Appendix for details). Despite these differences in relocation patterns, the table shows that establishment size, distribution across sectors, and workers' occupations are similar across these groups. Importantly, establishments across all relocation categories employ workers from every part of the metro area.

Commuting time data— The data include the municipality of residence for workers and municipality of location for the establishments, but not their street-level addresses. Consequently, we estimate commuting time to work using the official coordinates of both the worker's municipality of residence and the establishment's municipality. In most municipalities, these coordinates correspond to the location of the town hall, which is typically situated in the center. While using precise addresses would be preferable, Panel A in Figure 1 shows that the Paris metro area is fragmented into 1 268 different municipalities, which generally have a small land area, particularly in the inner suburbs. Importantly, for the municipality of Paris in the center, the data report location at the more detailed level of the 20 arrondissements, which are also represented in Figure 1.

To assess how relocations affect commuting time, we request route itineraries from transportation planners between each pair of municipalities in our sample. We obtain commuting time by public transportation from *Navitia.io*, a planner developed by a French National Railways company subsidiary, which calculates the fastest route by combining data from all available public transportation modes, including metros, suburban trains, tramways, and buses.[11] As discussed in Appendix A.3, we take into account changes in the transportation network over the period, described in Supplementary Appendix Table S1 and Figure S2, by requesting alternative routes from the planner. These changes affected 8% of requests. We also complement these data with the distance by road in km and commuting time by car during peak hours obtained

[11]The same data are used by popular commercial distance planners such as Google Maps or Mappy, and we have verified that our commuting times closely match those obtained from these websites.

from the METRIC database developed by the French statistical institute. Data Appendix A.3 provides further details on these datasets and the adjustments we performed.

3 Descriptive statistics

In this section, we document how, given the organization of the transportation network and differences in neighborhood characteristics across the metro area, relocations affect workers' commuting time and neighborhood quality.

Public transport organization— As in most metro areas, the mass rapid transit network is organized radially, which allows the center to be reached rapidly from all parts of the metro area. Panel B of Figure 1 shows that the center of Paris concentrates 244 out of 303 existing subway stations from 14 metro lines, which are connected with 15 suburban train lines that rapidly reach the outer suburbs (Mayer and Trevien, 2017). In contrast, no ring line connects different inner suburbs, making them more difficult to reach for workers commuting between suburbs. Employment is similarly concentrated, as illustrated in Panel C of Figure 1, with 31% of employees working in the center and 38% in the inner suburbs.

Differences in neighborhood quality— Neighborhood characteristics also vary dramatically within the metro area. We illustrate these differences in Panel D of Figure 1 using annual housing price data at the municipality and arrondissement level obtained from Bruneel et al. (2025). While being an imperfect proxy, a large literature has shown that differences in housing prices are strongly correlated with differences in amenities across neighborhoods (Gyourko et al., 1999). The figure shows that housing prices tend to be substantially higher in the center of the municipality of Paris, which concentrates the most affluent neighborhoods, best restaurants, theaters, and picturesque locations. In the inner suburbs, prices contrast significantly between the western suburbs, which host many wealthy municipalities, and historically industrial areas in the northern and southern suburbs, where prices are much lower and where newly developed business districts have recently emerged (Vieillard-Baron, 2011).

Consequences of relocations— Table 3 describes the main characteristics of the 2 787 identified relocations from 2006 to 2016, distinguishing as previously between relocations between

the suburbs and the center and those that result in a substantial change in the housing price rank of the municipality, which are likely to have a stronger effect on these two dimensions. Panel A of Table 3 shows that relocations from the center to the suburbs or from the suburbs to the center are not rare, accounting for 19% and 9% of our sample, respectively. Given the substantial differences in municipality characteristics documented earlier, a large share of relocations are associated with significant changes in local housing prices, with 24% involving a decline of more than one quartile in housing price rank and 28% involving the opposite increase. Panel B in Table 3 shows that establishments tend to relocate relatively far, 5 to 7 km from the initial location, which corresponds to an average of 38 minutes of commuting time by public transportation between their old and new locations. In the case of relocations from the center to the suburbs in particular, such a distance is associated with substantial changes in neighborhood characteristics as indicated by the average 38 percentile point decline in the housing price rank. In contrast, relocations from the suburbs to the center are associated with a 56 percentile point increase in the local housing price rank.

The concentration of the transportation network in the center also implies that relocations have a strong effect on employees' commuting time. Panel C in Table 3 shows that relocations from the center to the suburbs *increase* commuting time for more than 76% of their workers, leading to an 11-minute average increase in commuting time for incumbent employees present before and observed after the relocation, a 19% increase relative to the pre-relocation average of 57 minutes. In contrast, relocations from the suburbs into the center *decrease* commuting time for more than 65% of incumbent workers, leading to a 7-minute average decrease in commuting time. As neighborhoods with higher housing prices also tend to be better connected to the transportation network, a similar increase in commuting time is observed for relocations associated with a decline in housing price rank.

Such an increase in commuting time could be temporary if, following the relocation, establishments replace incumbent workers with long commutes by hiring workers who live closer, as predicted by competitive models. To assess this prediction, Figure 2 shows the evolution of the average commuting time of employees up to four years after the relocation, distinguishing between those hired before and after the relocation. In practice, workers hired after the relocation have commuting times very similar to those of workers hired before, with at most a 3-minute

difference between the two groups.

A final important result from Panel C in Table 3 is that the consequences of relocations on commuting time vary dramatically across incumbent workers. The table shows that the standard deviation in the change in commuting time ranges from 29 to 38 minutes. Large increases are not rare, as more than 10% of workers in establishments that relocate to the suburbs experience a commuting time increase greater than 30 minutes, leading to one additional commuting hour per day. These large differences in the effects of relocations on commuting time are exploited below in our individual-level estimates.

4 Econometric models

To assess how the previously highlighted changes in commuting time affect the outcomes of incumbent workers hired before the relocation, we consider the following model:

$$y_{ij,t} = \sum_{k=-2}^{2} \beta_k \cdot \mathbf{I}[k=t] \cdot \Delta CTime_{ij,t} + \eta_{jt} + \theta_{ot} + \alpha_{ft} + u_{ij,t} \tag{2}$$

where $y_{ij,t}$ is an outcome for worker i in establishment j observed in event year t, with $t = 0$ defined as the year in which the relocation occurred, $\mathbf{I}[k=t]$ is a dummy variable equal to one if the event year is equal to t and zero otherwise, and $u_{ij,t}$ is an error term. The parameters η_{jt}, α_{ft} and θ_{ot} represent establishment, fare zone changes and occupation by event year fixed effects. Our key explanatory variable is $\Delta CTime_{ij,t}$ which measures the change in commuting time by public transportation specific to worker i following the relocation of the establishment j, adjusted for the characteristics of the transportation network in event year t. This variable is calculated by fixing the municipality of residence to the one observed before the relocation, in order to account for the possibility of an endogenous change in place of residence after the relocation. As mentioned earlier, for most commuting routes, this variable is invariant across event years, except for about 8% of routes where the opening of a new Metro station or tramway line during our sample period affected commuting time.

Given that all parameters are specific to each event year, we estimate the models separately using OLS by event year. In particular, we estimate separate event coefficients β_k for each event year k over a five-year window, from two years before the relocation, to test for anticipation

effects, to three years after, to capture whether the consequences of relocations persist over time.[12] We report standard errors clustered at the establishment by event year level.

Employers might anticipate a relocation into a specific destination several years in advance and, as a consequence, might accordingly adjust the wages of workers hired just before the relocation. If such anticipation effects are empirically important, they should bias our estimates of β_k towards zero after the relocation. To address this concern, our baseline sample is restricted to workers with more than three years of tenure before the relocation year and who were less likely to anticipate the relocation when hired as a consequence.

Our first main outcome is the annual risk of separation, measured by a dummy variable equal to one if worker i is not observed in establishment j in event year t, conditional on being observed in the establishment in event year $t-1$. Our second main outcome is the change in log hourly wages relative to a reference year $r < t$ before the relocation, defined as $\Delta w_{ij,t} = w_{ij,t} - w_{ij,r}$ for worker i from establishment j in event year t. In our baseline estimates, we set the reference year to $r = -3$, that is, three years before the relocation, to address the concern that employers might adjust wages one or two years prior to the relocation in anticipation. To reduce the influence of outliers, we winsorize the top and bottom 1% of wage changes under each wage change definition. In addition, we provide separate estimates of the effects of relocations on the number of hours worked.

By using first differences in log hourly wages as outcomes, unobserved individual or firm-specific determinants of wages that are constant over time are eliminated. The inclusion of establishment-by-event-year fixed effects, η_{jt}, captures all common changes in wages or in job separation probability affecting all workers within an establishment similarly in a given event year, which implies that our parameters of interest are identified using within-establishment differences across workers.[13] The fare zone fixed effects α_{ft} account for the possibility that an establishment's relocation in a different fare zone may change the number of fare zones required for commuting by public transportation, which could in turn affect wages through the reimbursement by the employer of half of this additional cost as discussed earlier. Finally,

[12] In contrast to event studies using a discrete treatment, we do not need to normalize one coefficient. This is because, in each period k, the coefficient β_k is identified using within-establishment differences in commuting time increases across workers, rather than differences between treated and untreated establishments, as in a standard difference-in-differences setting.

[13] The inclusion of time-varying establishment fixed effect in the model implies that we cannot add any additional time-varying firm-level controls that do not vary across workers, such as the sector or the composition of employees in terms of occupations or gender, as they would be absorbed by this fixed effect.

occupation by event year fixed effects, θ_{ot}, account for the possibility that, due to the spatial segregation in residential locations within the metro area, different occupation groups experience systematically longer or shorter commuting time increases following a relocation. These fixed effects are defined using 404 three-digit level occupations. As demonstrated below, including occupation or fare zone fixed effects does not affect our estimates.

In our baseline specification, depending on whether the establishment moves closer or farther from the worker's place of residence, the explanatory variable $\Delta CTime_{ij}$ can be negative or positive, as in Mulalic et al. (2014). However, since firms may not reduce the wages of workers who benefit from a decrease in commuting time, we also estimate models that allow for different effects of increases and decreases in commuting time.

5 Baseline results

Column 3 in Table 4 reports estimates of the effects of commuting time changes on job separation and wages in the first year after the relocation. Overall, we find strong evidence that changes in commuting time affect not only the risk of job separation but also wages, consistent with the hypothesis that firms might compensate workers for longer commutes to retain them. A one-hour increase in commuting time, which corresponds to a two standard deviations increase according to Panel C in Table 3, is not only associated with a 2.2 p.p. increase in the risk of separation but also a 0.6% increase in hourly wages in the relocation year.

A concern with the previous result is that, as discussed earlier, commuting time increases and decreases might not affect wages symmetrically. This is especially true if workers are unwilling to accept wage cuts justified by the fact that the relocation decreased their commuting time. To investigate this hypothesis, we report estimates in column 4 allowing for separate effects of commuting time increases and decreases on workers' outcomes. For the risk of job separation, the two estimated effects appear to be broadly similar, suggesting that while longer commuting times increase the probability of separation, shorter commuting times symmetrically decrease the probability of leaving the firm. For wages, in contrast, the data strongly reject the hypothesis that increases and decreases have the same effect. On the one hand, the effect of an *increase* in commuting time is precisely estimated and twice as large relative to the baseline, indicating a 1.1% increase in hourly wages in response to one additional hour of

commuting. On the other hand, the estimated effect of a *decrease* in commuting time is practically zero and not statistically significant, suggesting that firms are not cutting the wages of employees who benefit from shorter commutes as a result of the relocation.

The lack of any negative effect of commuting time decreases on wages might reflect the fact that many workers are paid their base wage which is quite rigid. However, in separate estimates, we also find no evidence of effects of commuting time decreases on workers in highly paid occupations for whom wages are more flexible (not reported). Due to this asymmetry and for brevity, we only report estimates associated with increased commuting time when using hourly wages as an outcome in the remaining tables.

Medium-run estimates for event years $t = 1$ and $t = 2$ are reported in Columns 5 and 6 of Table 4, while longer-run effects, up to event year $t = 4$ for establishments observed until then, are reported in Supplementary Appendix Table S4.[14] For the risk of separation, the effects remain statistically significant up to event year 3. When combined across years, these estimates imply that a one-hour increase in commuting time is associated with a 5 p.p. increase in the risk of job separation over the three years. For wages, the coefficients remain statistically significant and broadly similar over the three years, up to event year $t = 2$. In later event years, Supplementary Appendix Table S4 shows that the coefficients are very close to zero, suggesting that the adjustment is concentrated in the first years after the relocation.

Validity of the empirical strategy— Our key identification hypothesis is that changes in commuting time resulting from an establishment's relocation do not affect workers in a way correlated with preexisting trends in wages or separation risks. To assess this hypothesis, we report 'placebo' estimates in the first two columns of Table 4, relating workers' outcomes observed one and two years before the relocation to future increases in commuting time associated with the relocation, using annual job separation probability as outcome in Panel A and hourly wages in Panel B. For both outcomes and all years, the estimated coefficients are near zero, allowing us to exclude any economically significant effect before the relocation. In Supplementary Appendix Table S4, consistent with earlier results, we find no effects of future commuting

[14] To measure outcomes over such a longer period, we instead use as a dependent variable for wages the annual change in log-hourly wages calculated between two event years. In addition, for the job separation probability only, we do not restrict workers to be present in the establishment in event year -3. Note that, as few establishments are observed over the entire 10-year period, their composition in the sample changes across years, even though establishments are still required to be observed for at least six years around the event, as previously.

time increases on either the job separation probability or annual hourly wage changes up to four event years prior to the relocation.

6 Differences across occupations and relocation types

We begin by reporting estimates examining the effects of relocations across occupation groups before examining relocations associated with substantial changes in neighborhood characteristics.

Differences across occupation groups— As discussed earlier, whether workers are compensated for longer commuting time may depend on how easily firms can replace them with workers living closer to the establishment. Since skilled workers are more costly to recruit (Blatter et al., 2012; Jäger and Heining, 2022), firms might be more inclined to raise their wages to retain them, and these workers may also be less likely to leave the establishment as a result. To assess this hypothesis, we report in Table 5 separate estimates for workers in low- or medium-paid occupations in column 2 and in highly paid occupations in column 3. Consistent with the hypothesis that workers in highly paid occupations might have stronger bargaining power, the estimated wage effects are strongly statistically significant for this group. In contrast, the effects of commuting time increases on the wages of workers in medium- or low-paid occupations are a third lower and not statistically significant. For the risk of separation, the pattern is reversed as we find larger effects of commuting time changes on workers in medium- and low-paid occupations compared to those in high-paying occupations.[15]

These differences by occupation groups translate into differences across establishments depending on their initial share of workers in highly paid occupations, which we measure using data from three years prior to the relocation. Results reported in columns 4 and 5 of Table 5 indicate that establishments with a higher share of workers in highly paid occupations are more likely to compensate their employees for increased commuting time. In such establishments, commuting time changes have a larger effect on wages but a much lower effect on job separation. In contrast, in establishments with a below-median share of workers in highly paid

[15]Unlike Le Barbanchon et al. (2021), who documented strong gender differences in disutility of commuting for unemployed workers, we find no significant gender differences in our sample of employed workers (results not reported).

occupations, commuting time changes have an effect more than three times as large on separation probability but no significant effect on wages. In the last two columns, we also report estimates in which firms are classified by using the 'poaching rank' proposed by Bagger and Lentz (2019). This index, which is in practice positively correlated with the share of workers in highly paid occupations, captures the attractiveness of the establishment using the fraction of its hires that are poached from other firms relative to the fraction coming from inactivity or unemployment. The results obtained with this classification are very similar: workers in establishments with an above-median poaching rank are less likely to quit the firm, while the effects on wages are also more precisely estimated.

Comparing relocations by change in neighborhood quality— The effects of commuting time increases may also depend on whether the new neighborhood offers better or worse characteristics relative to the previous one. If workers value locational amenities, commuting time increases should have a stronger effect in relocations that substantially downgrade neighborhood characteristics and little effect in relocations in which they improve. To assess this hypothesis, Panels A1 and B1 of Table 6 report separate estimates for relocations from the center into the suburbs, from the suburbs into the center, and for relocations in which the municipality's housing price rank increases or decreases by more than one quartile. Consistent with our hypothesis, commuting time increases associated with a downgrade in neighborhood amenities appear to have a stronger impact on both wages and the job separation probability. For wages in particular, the estimated coefficients are twice as large for this group of establishments. In contrast, for relocations likely associated with an improvement in neighborhood amenities, such as those into the center or those in which local housing price increases, we find lower or more imprecise effects of commuting time increases not only on wages but also on job separation probability.[16]

As mentioned earlier, high- and low-paid workers might value amenities in the center differently, as higher-income workers are more able to afford them. If this is the case, relocations to the center might have different effects on job separation across workers, as better amenities

[16]One concern is that our results might be due to the fact that relocations to the center are more typical of firms doing well while relocations to the suburbs are more likely to reflect economic difficulties. However, we find similar differences between relocations to the center and the suburbs when restricting the sample to firms with growing employment in the four years after the relocation. The share of firms with employment growth is also very similar between the two types of relocations.

in the center might be less likely to compensate the longer commutes of low-paid workers. To investigate this hypothesis, we report in Supplementary Appendix Table S5 separate estimates for relocations to the center by occupation groups. As previously, we also do not find any effect of commuting time increases on wages in these establishments relocating to the center. Even though the point estimates tend to be larger for lower paid workers, the effects of commuting time increase on the risk of separation are very close and not statistically significant for both groups of workers.

One important concern for these estimates is that, as discussed earlier, for about 8% of commutes in our sample, the opening of a new tramway line will decrease their commuting time in the future. These network changes might bias our estimates downward if establishments and workers anticipate that, in a few years, the expansion of the network is going to reduce commuting time to the establishment. In addition, at the local level, these network changes could also change the composition of inhabitants, thus affecting local amenities (Lee and Tan, 2024). For workers, they might also affect the commuting mode by reducing the probability of commuting by car (Mulalic and Rouwendal, 2020), thus affecting our commuting time measure. These effects might be particularly important for establishments relocating in the inner suburbs where most tramway openings are concentrated. To assess how much including commutes affected by future network changes influences our results, Panel A2 and B2 of Table 6 report separate estimates restricted to workers whose commutes, both before and after the relocation, are never affected by any network change, which includes about 92% of observations. Consistent with our hypothesis, excluding these observations substantially increases our wage estimates for relocations from the center into the suburbs and those associated with a housing price downgrade. For these relocations, the point estimates increase by about one-third, with one additional hour of commuting time raising hourly wages by 2.3%.

Other margins of adjustment— Since longer commuting time reduces the time available for leisure, relocations could also affect workers' labor supply. However, estimates using daily hours worked as a dependent variable in Panel A of Supplementary Appendix Table S6 are precisely estimated zeros across all event years and are not statistically significant. Relocations could also provide workers with incentives to change their place of residence to get closer to their new workplace. To assess this hypothesis, we examine in Panel B of Supplementary Ap-

pendix Table S6 whether commuting time increases are associated with a higher probability of changing the municipality of residence. To avoid our estimates being affected by changes in place of residence that might be driven by a change in employer, we restrict the sample to workers remaining in the establishment in the event year following the measured outcome. Overall, the estimates are statistically insignificant for most years and very close to zero, effectively ruling out any economically meaningful effect on this outcome. This lack of effect is not surprising given the substantial costs of residential mobility within the Paris metro area, combined with the abundance of potential employers, which always make it less costly for workers to find another employer than to relocate their residence.

Comparisons with existing estimates— While comparisons should be made with caution given the difference in context and empirical specification, our results are broadly similar to those of Mulalic et al. (2014) obtained using relocations across Denmark. The estimates reported in Panel B2 of Table 6 correspond to an increase in hourly wage for each additional (one-way) commuting hour ranging from 1.2% when all relocations are included in the sample to 2.3% for relocations from the center to the suburbs or those associated with one-quartile housing price downgrade. Assuming 8 hours of work per day, these increases correspond to a compensation of 10% to 18% of the initial hourly wage per additional hour of commuting.[17] Such estimates appears to be very close to the 16% estimate reported by Mulalic et al. (2014, p. 1098). With an average net hourly wage of about 30 euros in 2015, the average compensation thus ranges from 3 to 6 euros per additional hour of daily commuting.

7 Robustness

In this section, we provide evidence of the robustness of our main results to alternative specifications of the model, selection criteria of workers in the sample, or composition of establishments in the sample.

[17] Denoting by h the number of daily hours of work and $\hat{\beta}_m$ our estimates of the log hourly wage increase associated with one hour of additional one-way commuting, the corresponding additional daily earnings, in proportion to the initial hourly wage, associated with a one-hour one-way increase in commuting time is given by $\left(\exp(\hat{\beta}_m) - 1\right) h$ with $h = 8$ in our application.

Alternative commuting time measures— An important limitation of our data is that, since we do not observe precise addresses but only the municipality of departure and arrival, we use the center of each municipality as the departure and arrival points. To assess how much our results are affected by the uncertainty regarding the departure points, columns 2 and 3 of Table 7 report estimates using, alternatively, the maximum or minimum distance between each municipality pair. Reassuringly, the results obtained using these alternative measures are qualitatively similar and remain statistically significant, but the point estimates are about one-third smaller for both outcomes, suggesting that using these alternative measures might introduce additional attenuation bias.

A second important issue is that the commuting mode of the worker is not observed. As discussed earlier, even if according to census data 78% of workers employed in the center or inner suburbs commute by public transportation, commuting time by car, rather than by public transportation, might be the most relevant measure for workers living in the outer suburbs and working in the inner suburbs, for whom using their car might be much more efficient. To investigate this hypothesis, column 4 of Table 7 reports estimates based instead on the minimum commuting time between car and public transportation for each commute. Overall, while the estimates for the job separation probability tend to be substantially larger, the estimates for wages remain similar.

A more direct approach could be to use changes in the distance by road in kilometers between the two municipalities, as in Mulalic et al. (2014), as a measure of commuting time changes. For comparability, we divide this measure by 10, since a 10 km commute takes about 1 hour in the densest parts of the metro area. Results are reported in column 5 and are, once again, qualitatively similar to the previous estimates for the job separation probability, but they are not statistically significant for wages. However, these estimates appear to be more difficult to interpret in our context as the average speed per kilometer, whether by car or public transportation, varies considerably within the metro area, with speeds being two to three times higher in the inner suburbs compared to the center.

A straightforward way to assess how much the uncertainty regarding commuting time affects our result is to focus on workers living in the center and the inner suburbs, who are more likely to use public transportation than those living in the outer suburbs. Another advantage of

focusing on this group is that municipalities in the center or inner ring are much smaller in area than those in the outer ring, thus limiting measurement errors related to the points of departure and arrival. Consistent with the hypothesis that commuting times are better measured for these workers, estimates for wages restricted to this group reported in column 6 tend to be slightly larger and more precise.

Testing for nonlinearities— In Supplementary Appendix Table S7, we examine the presence of nonlinearities in the relationship between separation, wages, and changes in commuting time. We find little evidence of such nonlinearities, as estimates including a squared term are not substantially different, and the squared term is not statistically significant. We also find that estimates using changes in log commuting time yield similar results.[18] However, as discussed by Mulalic et al. (2014), changes in logs have the unattractive property of imposing the same effect for a 10-to-20-minute increase as for a 30-to-60-minute increase, which explains why we prefer to rely on changes in commuting time in levels as our baseline.

Robustness to alternative fixed effects— Our main identification hypothesis is that, within an establishment, changes in commuting time across workers are not systematically correlated with other unobserved factors influencing workers' outcomes. A simple and straightforward way to assess the validity of this identification hypothesis is to examine how our main results change when additional controls are progressively added to the regression. If commuting time changes are not systematically correlated with other factors that also influence wages or job separation, including more controls in the regression model should have little effect on the estimates. Estimates including an increasing set of controls are reported in Table 8. Column 1 includes only establishment fixed effects as controls.[19] In column 2, we add occupation fixed effects, and in column 3, we further include fare-zone fixed effects, as in our baseline model. Column 4 adds a gender dummy interacted with age and age squared. Reassuringly, the results are very similar across specifications.

[18]For an average worker with a 40-minute commute before the relocation (see Table 3), a 60-minute increase corresponds to a 0.91 log point increase. The estimates in Table S7 imply a 1.3 p.p increase in separation probability and a 0.9% increase in log hourly wages for this worker, which is quite close to our baseline results using commuting time in levels.

[19]For brevity, we do not report estimates without establishment fixed effects, as our identification hypothesis relies on the exogeneity of commuting time changes across workers *within* establishments, not between them. In practice, the estimated effects of commuting time increases are not statistically significant in estimates without fixed effects, for both wage and separation regressions.

Finally, column 5 adds to the model about a thousand additional municipality fixed effects for the worker's municipality or arrondissement of residence. These additional controls should absorb any systematic correlation between changes in commuting time and changes in wages that is common to workers living in the same municipality or arrondissement. Such correlations could arise, in particular, if establishments relocate strategically such that commuting time increases are less likely to affect workers living in wealthier parts of the metro area. In practice, even in such a demanding specification, the results remain largely unchanged.

Accounting for workers' selection— By construction, even though all workers in our previous estimates were observed in the establishment for at least three years prior to the relocation, the composition of the sample used for our prior estimates changes across event years, particularly after the relocation occurred, as some incumbent workers leave the establishment. One possibility is that only workers who benefited from wage increases correlated with commuting time changes, but driven by other factors, remained in the establishment after the relocation. If this hypothesis is correct, then we should also observe, prior to the relocation, a correlation between wages and future commuting time increases when the model is reestimated using only those workers who remained in the establishment after the relocation. To test this hypothesis, Supplementary Appendix Table S8 reports estimates using a balanced sample of workers who are continuously observed in the establishment over the six years of our sample. Compared to the baseline results in Panel B of Table 4, the estimates are very similar. Importantly, we also find no effect of commuting time changes on hourly wages in years preceding the relocation.

Differences across establishments— In Table 9, we investigate the robustness of our results to alternative selection of establishments in the sample. A first possibility is that some relocations may coincide with changes in the activities carried out at the establishments, in particular for large firms which possess multiple establishments in the metro area. One concern is that such reorganizations might also be associated with other unobserved changes affecting workers' utility or productivity. To investigate this issue, we identify establishments that concentrate more than 70% of the firm's total employment in the metro area both 3 years before and 3 years after the relocation from others. Because these establishments account for most of the firm's employment in the metro area, they are more likely to have maintained the same activities be-

fore and after the relocation. In practice, separate estimates for these two groups, reported in columns 2 and 3, provide very similar results, even though the estimates for wages tend to be more imprecise in establishments that account for less than 70% of the firm's total employment.

Another possibility is that, while many relocations might be driven by an expansion of the firm's activities, others may instead reflect economic difficulties and the need to reduce rental costs. Firms that are downsizing may have less incentive to compensate workers to preserve existing employment relationships. To assess this possibility, column 4 reports estimates excluding firms whose total employment in the Paris metro area declined over the four years following the relocation, while column 5 includes only firms with growing employment. Consistent with the hypothesis that expanding firms are more likely to compensate their workers, the estimated effects of commuting time increases on wages are measured more precisely in firms with positive employment growth. However, the differences between the two estimates for wages are minimal across both samples. In contrast, the effects of commuting time increases on job separation are about one-third larger in firms with declining employment.

8 Conclusion

To understand the trade-offs firms face when choosing an establishment's location, we investigated the consequences of establishments' relocations in the Paris metro area. We first documented that relocations in such a large metro area have a strong effect on workers' commuting time. Relocations between the center and the suburbs, in particular, are found to increase average commuting time by 19% for incumbent workers hired before the relocation. Consistent with the hypothesis that workers dislike commuting, we found strong evidence that these commuting time increases are associated with moderate but strongly significant higher risks of job separation while commuting time decreases are associated with a higher probability of remaining in the establishment. In response, firms increase the wages of workers who stay in the establishment but face longer commutes after the relocation. In contrast, they do not lower the wages of those whose commute becomes shorter. The impact of commuting time increases on wages also differs substantially across occupations as firms only adjust the wages of workers in highly paid occupations.

We also found that the effects of commuting time increases differ dramatically depending

on how the relocation affects the locational amenities of the municipality of the establishment. Establishments relocating to a municipality with lower levels of locational amenities, as measured by housing prices, offer a larger wage compensation for increased commuting time for their affected employees, who are also more likely to leave the establishment in response. In contrast, commuting time increases appear to have no significant effects on either the separation probability or wages when locational amenities improve substantially, such as for relocations from the suburbs into the center. Such differences suggest that workers value the locational amenities of their establishment such that better amenities might compensate for longer commuting times.

A significant limitation of our results is that our commuting time measure is imprecise as we used the municipality of the establishment and of the workers' residence to approximate commuting time. Another limitation is our measure of commuting time is subject to measurement errors, as we do not observe the commuting mode used by workers in the data. While such imprecision might introduce an attenuation bias in our estimates, we find our results to be robust to the use of many alternative commuting time measures.

Another limitation of our work is that our results are obtained by using a single metro area, Paris, as we do not have access to data that would allow us to replicate our study in other large metro areas. Finally, the increase in the possibility of working from home following the COVID-19 pandemic might have also diminished the importance of commuting time and of the locational amenities in workers' utility. We leave these issues for future work.

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A Appendix

A.1 Theoretical Appendix

Correlation between commuting time and wages under downward rigidity — We assume that $\Delta y_i = 0$ for simplicity. Denoting by γ the share of workers with a positive wage change $\Delta w_i > 0$, we have that $\gamma = Pr(c\Delta\tau_i - \Delta a > 0) = Pr(\Delta\tau_i > \Delta\tau_i^*)$. The law of total covariance implies that:

$$\begin{aligned}\text{cov}(\Delta w_i, \Delta\tau_i) = \quad & (1-\gamma)\text{cov}(\Delta w_i, \Delta\tau_i | \Delta\tau_i \leq \Delta\tau^*) + \gamma\text{cov}(\Delta w_i, \Delta\tau_i | \Delta\tau_i > \Delta\tau^*) + \\ & (1-\gamma)(\mathbb{E}(\Delta w_i | \Delta\tau_i \leq \Delta\tau^*) - \mathbb{E}(\Delta w_i))(\mathbb{E}(\Delta\tau_i | \Delta\tau_i \leq \Delta\tau^*) - \mathbb{E}(\Delta\tau_i)) + \\ & \gamma(\mathbb{E}(\Delta w_i | \Delta\tau_i > \Delta\tau^*) - \mathbb{E}(\Delta w_i))(\mathbb{E}(\Delta\tau_i | \Delta\tau_i > \Delta\tau^*) - \mathbb{E}(\Delta\tau_i))\end{aligned}$$

Denote Δw_i^R the change in wages under downward rigidity. When wages are downward rigid, then there exists a threshold change in commuting time, denoted by $\Delta\tau_i^* = \Delta a/c$, which directly depends on the change in amenities Δa. Specifically, $\Delta w_i^R = 0$ when $\Delta\tau_i \leq \Delta a/c$ and $\Delta w_i^R = \Delta w_i = (1-\eta)(c\Delta\tau_i - \Delta a)$ when $\Delta\tau_i > \Delta a/c$. This implies that $\text{cov}(\Delta w_i^R, \Delta\tau_i | \Delta\tau_i \leq \Delta\tau^*) = 0$ and $\mathbb{E}(\Delta w_i^R | \Delta\tau_i \leq \Delta\tau^*) = 0$. Using the law of total covariance and simplifying, we get:

$$\begin{aligned}\text{cov}(\Delta w_i^R, \Delta\tau_i) = \quad & \gamma(1-\eta)c \times \text{var}(\Delta\tau_i | \Delta\tau_i > \Delta\tau^*) + \\ & \gamma\mathbb{E}(\Delta w_i | \Delta\tau_i > \Delta\tau^*)(\mathbb{E}(\Delta\tau_i | \Delta\tau_i > \Delta\tau^*) - \mathbb{E}(\Delta\tau_i))\end{aligned}$$

The difference between the two covariances can thus be expressed by:

$$\begin{aligned}\text{cov}(\Delta w_i, \Delta\tau_i) - \text{cov}(\Delta w_i^R, \Delta\tau_i) = \quad & \\ (1-\gamma)\text{cov}(\Delta w_i, \Delta\tau_i | \Delta\tau_i \leq \Delta\tau^*) + & \\ (1-\gamma)(\mathbb{E}(\Delta w_i | \Delta\tau_i \leq \Delta\tau^*) - \mathbb{E}(\Delta w_i))(\mathbb{E}(\Delta\tau_i | \Delta\tau_i \leq \Delta\tau^*) - \mathbb{E}(\Delta\tau_i)) &\end{aligned}$$

Using the definition of Δw_i from Eq. 1, the first term becomes $(1-\gamma)(1-\eta)c \times \text{var}(\Delta\tau_i | \Delta\tau_i \leq \Delta\tau^*)$ and is therefore positive. In addition, since Δw_i is linearly increasing with $\Delta\tau_i$, we have that $\mathbb{E}(\Delta w_i | \Delta\tau_i \leq \Delta\tau^*) < \mathbb{E}(\Delta w_i)$ and $\mathbb{E}(\Delta\tau_i | \Delta\tau_i \leq \Delta\tau^*) < \mathbb{E}(\Delta\tau_i)$ which implies that the second term in the previous equation is also positive. This implies that $\text{cov}(\Delta w_i, \Delta\tau_i) \geq \text{cov}(\Delta w_i^R, \Delta\tau_i)$, in other words, that downward wage rigidity attenuates the covariance between wages and commuting time. The magnitude of this attenuation depends positively on $\Delta\tau^* = \Delta a/c$ which determines γ.

When firms prefer not to preserve the match — Even if the match remains profitable, firms might not be willing to preserve it if, after the relocation, they can find a similarly productive worker living closer to the firm and who will thus accept lower wages. To formalize this intuition, assume that firms can decide to dissolve the match and instead search for another worker with the same productivity y_i. However, once they have decided to dissolve the match, they can only receive one application per period and cannot be sure that the new match will be profitable. Assuming the firm is risk neutral and profits are zero if they match with a worker with a commuting time exceeding τ^*, the expected profit from a new match is $J_{new} = \int_0^{\tau^*}(1-\eta)(y_i - c\tau + a' - b)dG(\tau)$ where $G(.)$ denotes the cumulative distribution function of the distribution of commuting time in the new location. Denoting by J_{old} the profits from the existing match, the firm prefers to search for another worker after the relocation if: $J_{new} \geq J_{old}$ which simplifies to $c\left(\tau_i' - \int_0^{\tau^*}\tau dG(\tau)\right) \geq (1-G(\tau^*))(y_i + a' - b)$. The previous expression indicates that firms will look for another worker when the wage decrease associ-

ated with the lower expected commuting time of the new worker is greater than the decrease in expected profit associated with the uncertainty of finding a worker. When most matches are profitable such that $G(\tau^*)$ is close to one, the previous condition depends solely on whether the commuting time of the worker in the existing match is superior to the expected commuting time from matching with a new worker.

A.2 Data appendix

Variables used to match workers over time — For each year t, the files report information on establishment ID, gender, number of hours, job duration in days, start and end dates of the job, municipality of work and residence, earnings and age, for both year t and $t-1$. We use programs from Babet et al. (2025), accessible online on their website (Godechot, 2025) to match workers over time using these variables and create a panel. A limitation of this procedure is that, as it exploits annual retrospective information, a worker cannot be matched between two years if she does not work at least one day in each year. If they reenter the sample later, the algorithm assigns them another identifier.

Establishments' selection — We exclude establishments from the Construction or Transportation sectors, as their workers typically do not work at the establishment's location. We also exclude establishments from the Wholesale and Retail Trade sectors that sell their products locally. In addition, we have eliminated two large establishments with more than 2 500 workers in which all workers were erroneously declared as working at the head office instead of being declared separately in each establishment. Our main sample therefore includes the following four one-digit sectors: Manufacturing, Information and Communication, Finance and Insurance, Professional, Scientific and Technical Services, and Administrative and Support Services.

Sample selection — Following Babet et al. (2025), we exclude jobs with an hourly wage below 80% of the legal minimum hourly wage for the corresponding year (0.1% of observations) or above 100 times the minimum hourly wage (0.01%).

Occupation group classification — We use the French occupational classifications at the one-digit level to group workers into two main skill groups. *Low- and medium-paid occupations* correspond to Agricultural Workers, Craft and Related Trades Workers, Plant and Machine Operators and Assemblers, and Elementary Occupations, Technicians and Associate Professionals, Clerical Support Workers, Services and Sales Workers. *Highly paid occupations* correspond to Managers and Professionals.

Housing price data — We use annual housing price data at the municipal and arrondissement levels, collected and processed by Bruneel et al. (2025) to calculate housing price ranks across municipalities and arrondissements of the center and inner suburbs of the Paris metro area. For the period from 2000 to 2010, the data rely on the BIEN dataset, which quasi-exhaustively records all real estate transactions. From 2015 onward, the data are based on the DV3F dataset published by CEREMA, which replaced the BIEN database and also provides comprehensive transaction records. We use housing prices adjusted for surface area, number of rooms, and year of construction. See Bruneel et al. (2025) for details on the adjustment.

Classification of relocations — Throughout the paper, we focus on relocations within the center and inner suburbs ('petite couronne') thus including the municipality of Paris and the three departments of the inner ring, Seine-Saint-Denis, Val-de-Marne, and Hauts de Seine. We

separately categorize relocations between the municipality of Paris and the suburbs relative to those occurring within the inner suburbs or the municipality of Paris. Relocations are further categorized by how they change the housing price rank of the municipality of departure and destination. Among relocations from the suburbs to the center, we concentrate on the 90% that are associated with an increase in housing price rank of more than one quartile to facilitate interpretation. Housing price ranks are always calculated by weighting municipalities according to their number of workers in the relocation sample. Separate housing price ranks are calculated for each calendar year.

A.3 Commuting time measurement

Collecting commuting time data— Commuting times are requested on trajectory planners using the official coordinates of the municipality of residence of the worker as a departure point and those of the establishment as the arrival point. For commuting time by car, we use the 2018 version of the Metric database (INSEE, 2018). For public transportation, we use itinerary planners and request commuting times for itineraries starting on Monday at 8 a.m. Our main data are based on requests made in 2019 on the publicly provided *Navitia* API. To identify commuting affected by the opening of a metro station or tramway lines reported, we supplemented these initial data with additional requests realized between December 2024 and January 2025 using the *Idf mobilité* API, which had replaced Navitia. Note that we prefer to use our 2019 commuting data as a baseline as it is closest to our period of interest and it is not affected by the opening of new stations that occurred just before the 2024 Olympic games in Paris. In the additional requests performed between 2024 and 2025, we collected detailed information on the transportation modes and lines used during the journey. For commuting in the same municipality as the municipality of residence, we impute 10 minutes of commuting time.

Adjusting for network changes — Changes in the transportation network over the period meant that one transportation mode was not available in the relevant year. These changes, described in Supplementary Appendix Table S1 and Supplementary Appendix Figure S2, included the opening of five metro stations on existing lines and the extension or creation of 9 new tangential tramway lines in the inner suburbs. Using data on transportation modes used during the journey, we identify that 6% of commutes before the relocation and 8% after are affected by a change in the available commuting mode for the shortest route, leading to 12% of commuting time *changes* affected. When a commuting mode is not available, we request an alternative trajectory from the API that uses only commuting modes available in that year, which we obtain for 92% of observations affected by a change. For the remaining observations, for which no alternative trajectory is proposed by the calculator, we use commuting times with and without the new mode to estimate how much it affects commuting time. To impute missing commuting times, we use separate linear regressions for each new metro station and tramway line, using commuting time as a dependent variable and controlling for the distance in km in addition to a dummy capturing the effect of the new mode of transportation on commuting.

Minimum and maximum commuting time — We developed a perimeter-sampling approach to identify the minimum and maximum distance between two municipalities. Specifically, we divided the border of each municipality into 12 evenly separated points and computed all pairwise distances between these points for every municipality pair. The minimum and maximum of these distances were recorded. For each of these pairs, we requested commuting time by public transportation using the Navitia API.

A.4 Fare zones and commuting costs

Reimbursement of travelcards by Employers — Since 1982, the law mandates that all employers of establishments located in the Paris metro area to reimburse half of the subscription cost of the monthly or annual travelcard passes subscribed by their employees. The amount reimbursed depend on the number of fare zones crossed during the journey which determines the subscription cost. The reimbursement is directly made each month on the wage bill of the employee, provided that a subscription and payment certificate can be presented upon request. The DADS data we use does not separately report this reimbursement from the wage bill.

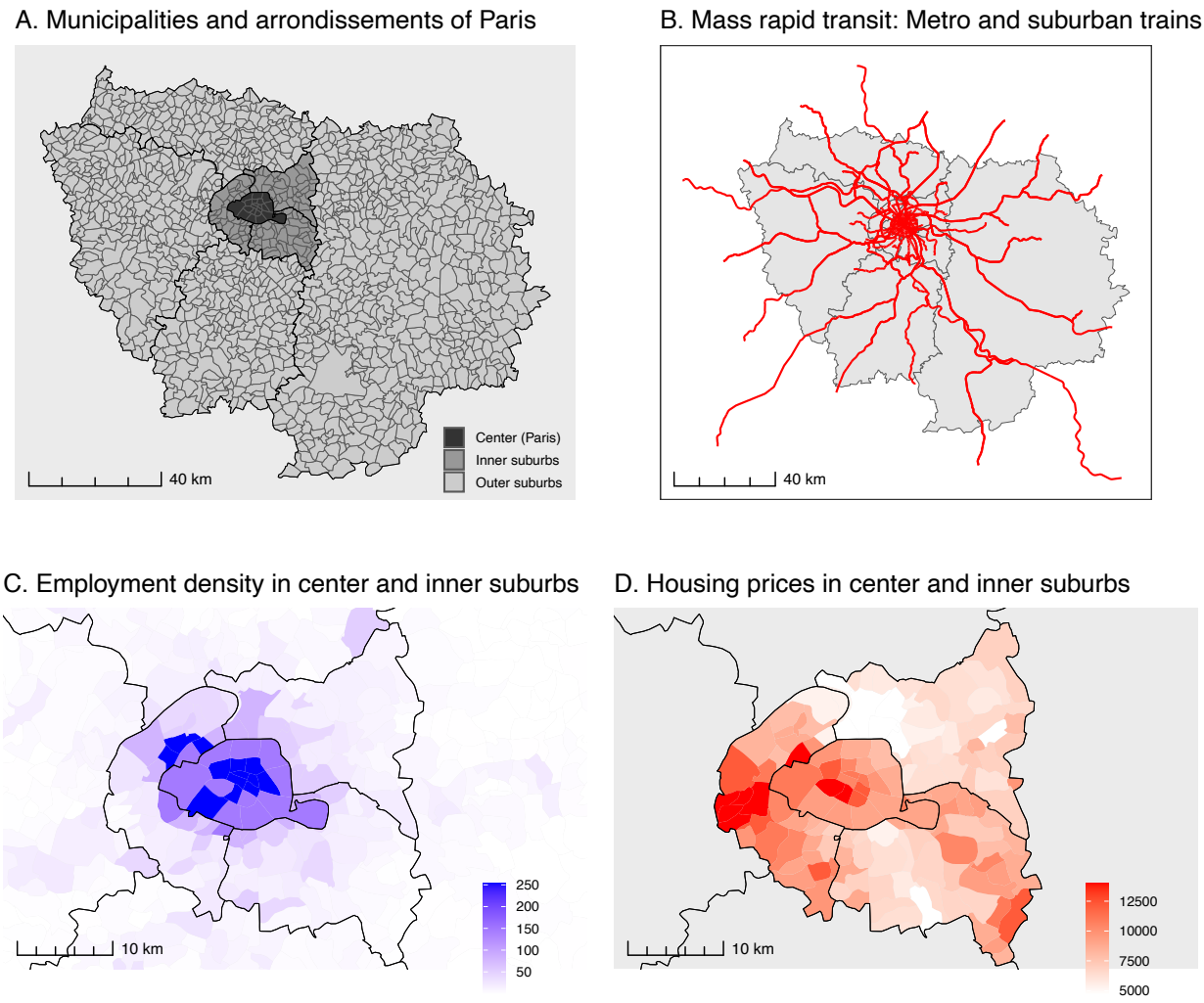
Effects of relocations on fare zones — Relocations between the center and the suburbs might change the number of fare zones in travelcard subscriptions required to commute from the place of residence to work. The Paris metro area is divided into six distinct fare zones, which are arranged concentrically at an increasing distance from the center. As we focus on relocation within the center and inner suburbs, an establishment can only be located in three fare zones: the center (zone 1), the inner suburbs close to Paris (zone 2), and the inner suburbs at the outskirts of the inner ring (zone 3). All travelcard subscriptions always bundle zone 1 with zone 2 as these are the zones corresponding to the metro network which cannot be subscribed to separately. As a result, only relocations between zone 3 and zones 1 or 2 will in practice increase or decrease the number of fare zones. Over our sample period, the additional cost of adding zone 3 to the monthly travelcard subscription varied between €15 in January 2003 to €19 in January 2015 (LégiSocial, 2014). This additional cost translates into a mandated additional reimbursement of up to €10 maximum from the employer, which is paid directly through the employee's wage bill. In September 2015, a reform eliminated all fare zones, so that after this date, any subscription including the center also includes all other zones in the metro area, including the outer suburbs. Note that, over the period, even after the September 2015 reform, workers in the outer suburbs who do not cross the center during their commute have the option to subscribe to travelcards that do not include zone 1 or 2 but include zone 3 and at least another zone from the outer ring. As a result, relocations could also affect the number of zones for some workers from the outer suburbs. In practice, such subscriptions are very marginal as they do not allow workers to take the metro in addition to not crossing the center, accounting for less than 2% of total subscriptions before the 2015 zoning reform (about 6% of workers in the outer suburbs), and less than 1% thereafter (Omnil, 2024).

Construction of fare zone fixed effects — For workers living in the center or inner suburbs (zones 1 or 2), we construct two fare zone change fixed effects: one for relocations from zones 1 or 2 to zone 3, and another for relocations from zone 3 to zones 1 or 2. For workers in the outer suburbs (zone > 3), we construct analogous fixed effects for relocations between zones 1 or 2 and zone 3 and another for relocations from zone 3 to zones 1 or 2.

Figures and Tables

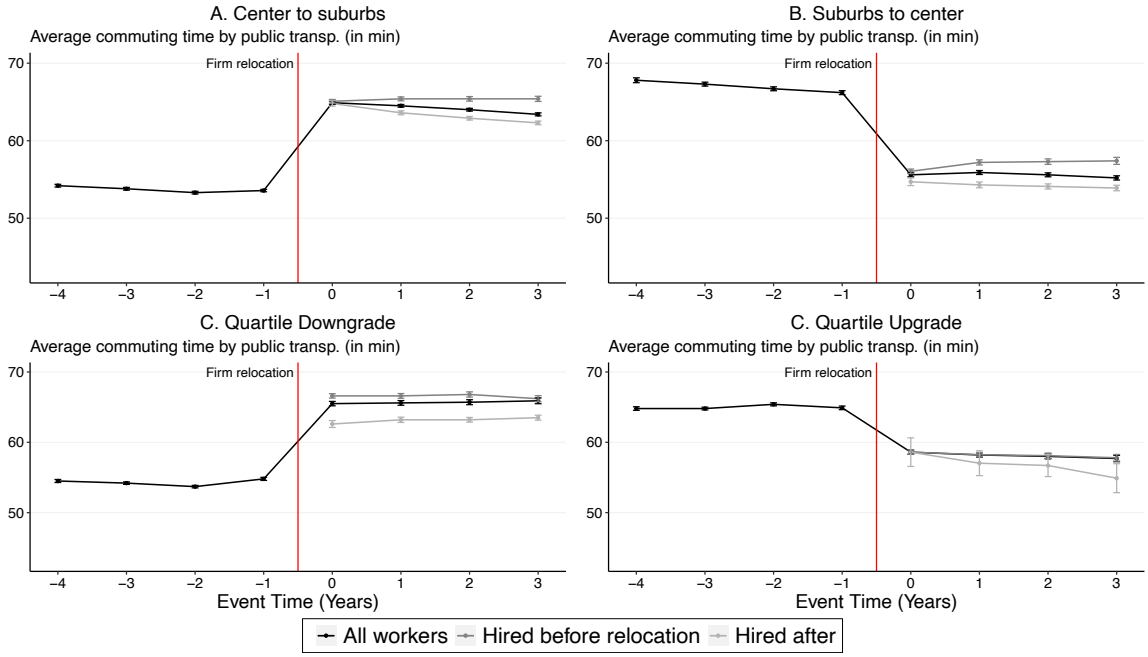
Figures

Figure 1: Main characteristics of the Paris Metro Area



Sources: Maps from Geofla database. Wage data from DADS 2010-2018. *Notes:* The Paris metro area is defined using the boundaries of the Ile-de-France region. The center and inner suburbs are defined using the department of Paris and the three surrounding departments. Panel A shows the administrative boundaries of municipalities in the metro area and of the 20 *arrondissements* within the municipality of Paris. Panel B shows, in red, the mass rapid transit lines, metros, suburban trains and tramways. Panels C and D show, respectively, the number of employees per hectare and the housing price per square meter in 2019 across municipalities and arrondissements in the center and inner suburbs. For readability, both distributions are summarized using 20 quantiles.

Figure 2: Consequences of relocations on average commuting time



Sources: DADS data 2003-2018. *Notes:* Panels A to D show the evolution of average commuting time by public transportation by event year, for up to four years before and after the relocation, for the indicated type of relocation. After the relocation, the panels also report separately the average commuting times of workers hired before and after the relocation. Panel A considers establishments that relocate from the center to the inner suburbs, and Panel B those relocating from the inner suburbs to the center. Panel C considers establishments for which the housing price rank of the municipality decreases by more than a quartile after the relocation, while panel D considers those in which the housing price rank increases by more than a quartile.

Tables

Table 1: Comparison of Relocating and Non-Relocating Establishments

Establishment type	Non-Relocating Establishments	All Relocations
Median Number of Employees (Before Relocation)	277	134
Average employee age	39.8	39.6
Share women among employees	43.5	47.7
Median log hourly wages	3.05	3.35
	A. Sectoral Composition (%)	
Information and Communication	18.4	23.6
Finance and Insurance	20.7	21.4
Professional, Scientific, and Technical Services	46.8	42.9
Administrative and Support Services	14.1	12.1
	B. Employment Composition (%)	
Low- and Medium-Paid Occupations	44.7	36.7
Highly Paid	55.3	63.3
	C. Worker Residence Distribution (%)	
Paris center	23.3	28.6
Inner suburbs	45.2	41.3
Outer suburbs	31.4	30.1

Source: DADS data 2003-2018. *Note:* The table compares non-relocating establishments (column 1) and relocating establishments (column 2). The sample includes private-sector establishments with more than 20 employees, located in the center or inner suburbs of Paris, excluding those in Hospitality, Wholesale, and Retail Trade. Relocating establishments are defined as those that relocated between 2006 and 2017 within the center or inner suburbs of the Paris metro area. For relocating establishments, the data correspond to the year of relocation. For non-relocating establishments, average characteristics are calculated by pooling data from 2007, 2012 and 2017. Median hourly wages are deflated using the consumer price index. Panel A reports the sectoral distribution. Panel B reports the share of workers across occupation groups. Panel C reports the share of workers residing in different parts of the metro area.

Table 2: Comparison of Relocating Establishment Characteristics

	Relocating Establishments by Direction and Housing Price Change			
	Center to Suburbs	Suburbs to Center	Quartile Housing Price Downgrade	Quartile Housing Price Upgrade
Median Number of Employees (Before Relocation)	146	124	132	121
Average employee age	40.2	40.5	40.6	39.2
Share women among employees	48.4	46.4	51.0	47.5
Median log hourly wages	3.33	3.32	3.35	3.34
	A. Sectoral Composition (%)			
Information and Communication	22.2	28.0	20.0	27.7
Finance and Insurance	23.0	26.4	26.5	20.6
Professional, Scientific, and Technical Services	40.6	36.4	41.3	43.4
Administrative and Support Services	14.2	9.3	12.3	8.3
	B. Employment Composition (%)			
Low- and Medium-Paid Occupations	35.3	34.1	34.2	38.4
Highly Paid	64.7	65.9	65.8	61.6
	C. Worker Residence Distribution (%)			
Paris center	32.3	25.8	31.5	27.8
Inner suburbs	38.3	43.1	38.9	41.9
Outer suburbs	29.3	31.1	29.6	30.2

Source: DADS data 2003-2018, Navitia and Metric. *Note:* The table compares relocating establishments depending on the characteristics of their municipality of departure and arrival. The sample includes private-sector establishments with more than 20 employees, located in the center or inner suburbs of Paris, excluding those in Hospitality, Wholesale, and Retail Trade. Relocating establishments are defined as those that relocated between 2006 and 2017 within the center or inner suburbs of the Paris metro area. Column 1 includes relocations from the center to the suburbs, and column 2 from the suburbs to the center . Column 3 includes relocations where the housing price rank decreased by more than one quartile; column 4, where it increased by more than one quartile. Median hourly wages are deflated using the consumer price index. Panel A reports the sectoral distribution. Panel B reports the share of workers across occupation groups. Panel C reports the share of workers residing in different parts of the metro area.

Table 3: Characteristics of relocations

Relocation Direction	All Relocations	Center to Suburbs	Suburbs to Center	Quartile Housing Price Downgrade	Quartile Housing Price Upgrade
A. Characteristics of establishment relocation					
Number of Establishments	2,787	532	257	676	779
Share of All Relocation (%)	100.0	19.1	9.2	24.3	28.0
Median Number of Employees (Before Relocation)	133	161	123	132	108
Median Number of Employees (After relocation)	203	277	237	275	192
B. Difference Between the Old and New Locations					
Distance (km)	5.1	5.8	7.3	6.0	5.7
Public Transit Time (minutes)	37.4	39.6	44.5	40.7	40.0
Change in housing price rank	-0.1	-37.7	55.9	-47.5	46.5
C. Distribution of Public Transit Commuting Time Changes for Employees					
Average Change	2.7	10.6	-6.7	9.6	-3.4
Share with Increased Commute Time (%)	56.3	76.2	34.5	72.5	40.4
Standard deviation (minutes)	30.8	29.1	38.0	29.6	33.8
10th Percentile	-19.9	-11.6	-33.9	-12.4	-27.7
Median change	2.5	11.6	-8.4	9.8	-3.8
90th Percentile	25.5	30.5	23.4	30.6	22.0

Source: DADS data 2003-2018, Navitia and Metric. *Note:* The Table reports the characteristics of establishments relocating within the Paris metro area. Relocating establishments are defined as those that relocated between 2006 and 2017 within the center or inner suburbs of the Paris metro area. Column 1 includes all relocations; column 2 relocations from the center to the suburbs; column 3 from the suburbs to the center; column 4, for relocations in which the housing price rank decreased by more than one quartile; and column 5, in which the housing price rank increased by more than one quartile. Panel A reports the number of establishments, and the number of employees before and after the relocation. Panel B reports the distance in km, the public transit time between locations, and the average change in housing price rank of the municipality. Panel C reports the distribution of commuting time changes via public transportation for incumbent workers remaining in the establishment including the average change, the share of workers experiencing increased commuting time, the standard deviation, and the 10th, median, and 90th percentiles.

Table 4: Effects of commuting time on job separation and wages

Outcome	A. Annual job separation probability					
Event year	-2	-1	0	0	1	2
ΔCommuting time	0.000	0.000	0.022***			
	(0.003)	(0.001)	(0.005)			
ΔCommuting time > 0				0.021***	0.019**	0.012
				(0.006)	(0.008)	(0.008)
ΔCommuting time < 0				0.024**	0.015	0.012
				(0.009)	(0.009)	(0.009)
N	256,493	250,549	243,584	243,584	122,080	108,051
R2	0.06	0.20	0.48	0.48	0.14	0.19
	B. Log hourly wage change relative to event year t= −3					
ΔCommuting time	0.001	0.003	0.006**			
	(0.001)	(0.002)	(0.003)			
ΔCommuting time > 0				0.011***	0.012***	0.011**
				(0.004)	(0.005)	(0.005)
ΔCommuting time < 0				0.000	-0.002	-0.006
				(0.005)	(0.006)	(0.006)
N	247,339	243,584	122,455	122,455	106,980	90,899
R2	0.20	0.17	0.22	0.23	0.24	0.24

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is the annual separation probability (Panel A) and the change in log-hourly wage relative to event year -3 (Panel B) in the indicated event year. The explanatory variable is the change in commuting time by public transportation due to the relocation, measured in hours. Columns 1 and 2 display placebo regressions on outcomes occurring two and one year before the relocation. Other columns report estimates for the relocation year and one and two years post-relocation. The last three columns report separate estimates for the effects of commuting time increases and decreases. Only workers present for at least three years before the relocation and establishments observed over the six event years are included in the sample. All regressions include establishment by event year, occupation by event year and fare zone changes fixed effects. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.

Table 5: Effects of commuting time by occupation groups and establishment composition

	Baseline: All workers & establishments	Low & Medium paid Occupations	Highly paid occupations	Share highly paid occupation in establishment		Poaching rank of establishment	
				Below median	Above median	Below median	Above median
	A Job separation probability in relocation year						
ΔCommuting by public transportation	0.022***	0.027***	0.019**	0.036***	0.010**	0.035***	0.013**
	(0.005)	(0.005)	(0.004)	(0.007)	(0.004)	(0.005)	(0.004)
N	243,584	85,818	157,766	111,813	131,771	114,199	129,395
R2	0.47	0.49	0.48	0.47	0.49	0.46	0.50
	B. Log hourly wage change in relocation year relative to t = –3						
ΔCommuting by public transportation > 0	0.011***	0.007	0.011**	0.007	0.016**	0.011	0.012**
	(0.004)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)
N	122,455	43,734	78,721	58,567	61,708	57,974	62,301
R2	0.22	0.25	0.26	0.22	0.25	0.25	0.22

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is the annual separation probability in the relocation year (Panel A) and the change in log hourly wage relative to event year -3 (Panel B). The explanatory variable is the change in commuting time by public transportation due to the relocation measured in hours, using only increases in Panel B. Column 1 reports baseline results including all establishments and workers. Columns 2 and 3 show results for workers in low/medium- and highly paid occupations. Columns 4 and 5 show results for establishments with below- and above-median shares of workers in highly paid occupations three years before the relocation. Columns 6 and 7 show results for establishments with below- and above-median poaching rank three years before the relocation. The poaching rank is defined as the share of newly hired employees that were working for another employer when hired. Only workers present for at least three years before the relocation and establishments observed over the six event years are included in the sample. All regressions include establishment by event year, occupation by event year, and fare zone changes fixed effects. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.

Table 6: Effects of commuting time across relocation type

Relocation types	Baseline All Relocations	Suburbs to Suburbs or Center to Center	Center to Suburbs	Suburbs to Center	Quartile Housing Price Downgrade	Quartile Housing Price Upgrade
	A. Dependent variable: Job separation probability in relocation year					
	A1 All commuting changes					
ΔCommuting time	0.022***	0.023***	0.024***	0.014	0.026***	0.015
	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)	(0.011)
N	243,584	170,010	49,730	23,844	55,198	51,153
R2	0.49	0.48	0.44	0.44	0.56	0.43
	A2 Only commuting without network change					
ΔCommuting time	0.027***	0.028***	0.027***	0.016	0.030***	0.014
	(0.006)	(0.007)	(0.010)	(0.011)	(0.009)	(0.012)
N	223,343	154,882	45,968	22,493	50,227	47,658
R2	0.49	0.48	0.55	0.44	0.57	0.44
	B. Dependent variable: Log hourly wage change in relocation year relative to t = –3					
	B1 All commuting changes					
ΔCommuting time > 0	0.011***	0.010	0.017**	0.005	0.011	0.006
	(0.004)	(0.006)	(0.007)	(0.010)	(0.008)	(0.008)
N	122,455	83,653	26,306	12,496	27,551	26,657
R2	0.22	0.22	0.21	0.28	0.20	0.27
	B2 Only commuting without network change					
ΔCommuting time > 0	0.012**	0.008	0.023***	0.006	0.021***	0.008
	(0.005)	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)
N	112,191	76,021	24,358	11,812	24,822	24,811
R2	0.23	0.23	0.21	0.28	0.20	0.27

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is annual separation probability in the relocation year (Panel A) and the change in log hourly wage relative to event year -3 (Panel B). The explanatory variable is the change in commuting time by public transportation due to the relocation measured in hours, using only increases in Panel B. Panels A1 and B1 include all commuting time changes, Panels A2 and B2 exclude those affected by future network changes during the sample period. Column 1 includes all relocations. Column 2 includes relocations within suburbs or within the center. Column 3 includes relocations from center to suburb, and column 4 from suburbs to center. Column 5 includes relocations where the housing price rank decreased by more than one quartile; column 6, where it increased by more than one quartile. Only workers present for at least three years before the relocation and establishments observed over the six event years are included in the sample. All regressions include establishment by event year, occupation by event year, and fare zone changes fixed effects. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.

Table 7: Robustness to alternative measures of commuting time

	A. Job separation probability in relocation year					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔCommuting time by public transportation	0.022***					0.024***
	(0.005)					(0.006)
ΔCommuting time by public transportation: minimum distance between municipalities		0.017***				
		(0.004)				
ΔCommuting time by public transportation: maximum distance between municipalities			0.016***			
			(0.003)			
ΔMin commuting time (car, public transport)				0.038***		
				(0.008)		
Δkm/10					0.018***	
					(0.005)	
N	243,584	243,584	243,584	243,584	243,584	165,240
R2	0.48	0.48	0.48	0.48	0.48	0.48
	B. Log hourly wage changes in relocation year relative to t = −3					
ΔCommuting time by public transportation>0	0.011***					0.015***
	(0.004)					(0.005)
ΔCommuting time by public transportation >0 minimum distance between municipalities		0.007**				
		(0.003)				
ΔCommuting time by public transportation >0 maximum distance between municipalities			0.008**			
			(0.003)			
Δ Min commuting time (car, public transport)				0.011**		
				(0.006)		
Δkm/10 >0					0.003	
					(0.003)	
N	122,455	122,455	122,455	122,455	122,455	82,974
R2	0.22	0.22	0.22	0.22	0.22	0.24
Sample	All workers	All workers	All workers	All workers	All workers	Only residents in center and inner suburbs

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is annual separation probability in the relocation year (Panel A) and the change in log hourly wage relative to event year −3 in the relocation year (Panel B). The explanatory variables are alternative measures of the change in commuting time due to the relocation, using only increases in Panel B. Column 1 reports our baseline estimates using commuting time by public transportation. Columns 2 and 3 use alternative measures of commuting time based on the minimum and maximum distance between two municipalities. Column 4 uses the minimum commuting time by car or public transportation, column 5 uses the change in distance in km divided by 10. Column 6 restricts the sample to workers living in the center and inner suburbs. Only workers present for at least three years before the relocation and establishments observed over the six event years are included in the sample. All regressions include establishment by event year, occupation by event year, and fare zone changes fixed effects. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.

Table 8: Robustness to alternative fixed effect inclusions

	(1)	(2)	(3)	(4)	(5)
Outcome	A. Job separation probability in relocation year				
ΔCommuting by public transportation	0.023***	0.023***	0.022***	0.023***	0.020**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N	243,584	243,584	243,584	243,584	243,584
R2	0.48	0.48	0.48	0.49	0.49
	B. Log hourly wage change in relocation year relative to t = −3				
ΔCommuting by public transportation>0	0.011**	0.011***	0.011***	0.010**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
N	122,455	122,455	122,455	122,455	122,455
R2	0.21	0.22	0.22	0.26	0.27
Establishment fixed effects (2500)	Yes	Yes	Yes	Yes	Yes
Occupation fixed effects (364)	No	Yes	Yes	Yes	Yes
Fare zone changes fixed effects (5)	No	No	Yes	Yes	Yes
Worker's gender interacted with age and age squared	No	No	No	Yes	Yes
Municipality fixed effects (983)	No	No	No	No	Yes

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is annual separation probability in the relocation year (Panel A), and the change in log hourly wage relative to event year −3 (Panel B). The explanatory variable is the change in commuting time by public transportation due to the relocation measured in hours, using only increases in panel B. Column 1 includes only establishment fixed effects. Column 2 adds occupations fixed effects. Column 3 further includes fare zone change fixed effects. Column 4 adds a dummy for the worker's gender interacted with age and age squared. Column 5 adds municipality fixed effects. Only workers present for at least three years before the relocation and establishments observed over the six event years are included in the sample. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.

Table 9: Robustness to alternative establishment selection

	(1)	(2)	(3)	(4)	(5)
Specification	Baseline	Establishment with ≥70% of firm's total employment	Establishment with <70% of firm's total employment	Firms with employment growth	Firms with employment decline
Outcome	A Job separation probability in relocation year				
ΔCommuting by public transportation	0.022***	0.016***	0.028***	0.019***	0.027***
	(0.005)	(0.006)	(0.008)	(0.005)	(0.008)
N	243,583	115,918	127,666	136,163	107,421
R2	0.47	0.27	0.49	0.55	0.38
	B Log hourly wage change in relocation year relative to t = –3				
ΔCommuting by public transportation>0	0.011***	0.011**	0.012	0.012**	0.010
	(0.004)	(0.005)	(0.007)	(0.005)	(0.006)
N	122,455	84,646	37,809	65,421	63,908
R2	0.22	0.21	0.25	0.25	0.22

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is the annual separation probability in the relocation year (Panel A), and the change in log hourly wage relative to event year -3 in the relocation year (Panel B). The explanatory variable is the changes in commuting time due to the relocation measured in hours, using only increases in panel B. Column 1 reports the baseline estimates. Columns 2 and 3 report separate estimates for establishments that account for more or less than 70% of the firm's total employment in the metro area, measured both three years before and three years after the relocation. Columns 4 and 5 report estimates excluding or focusing on firms whose total employment in the Paris metro area declines by more than 20% across establishments over the four years following the relocation. Only workers present for at least three years before the relocation and establishments observed over the six event years are included in the sample. All regressions include establishment by event year, occupation by event year and fare zone changes fixed effects. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.

Supplementary Appendix to:

Will You Follow me to the Suburbs? The Consequences of Establishments' Relocation in a Large Metro Area

Gregory Verdugo Malak Kandoussi

This Supplementary Appendix presents additional information to complement Kandoussi and Verdugo (2025). In section S1, we provide evidence on the quality of work hours reported by employers in the DADS data following the approach suggested by Lachowska et al. (2022). Sections S2 and S3 present additional Figures and Tables that are referred to in the main text but not essential to the reader's comprehension.

S1 Validity of work hours in DADS data

Following Lachowska et al. (2022), we report two empirical tests regarding the quality of hours of work in the DADS data: *(i)* First, we study the correlation between annual changes in log earnings and yearly changes in the log of paid hours between two consecutive years. *(ii)* Second, we study how the distribution of hourly wages responds to annual increases in the minimum wage.

S1.1 A regression-based test of signal-to-noise in hours data

To capture the correlation between annual changes in log earnings and changes in log hours for workers, we estimate the following linear model using a sample of workers who did not change employers:

$$\Delta log(earn_{it}) = \beta_0 + \beta_1 \Delta log(hours_{it}) + \varepsilon_{it} \tag{S1}$$

where $\Delta log(earn_{it})$ is the annual change in log annual earnings for individual i in period t, $\Delta log(hours_{it})$ is the annual change in log hours and ε_{it} is an error term.

As discussed by Lachowska et al. (2022), if hours are measured accurately and all workers are paid by the hour, estimates of the coefficient β_1 should be close to 1. However, in a practical scenario, the coefficient should be attenuated by the fact that the sample also includes workers with a fixed number of hours or who are not paid hourly. Estimation results are reported in Table S2 for different years in our sample. Across these specifications, the estimated slope coefficients range from 0.84 to 0.86, which is very similar to the estimate of 0.8 reported by Lachowska et al. (2022) using administrative data from the State of Washington in the US. Notably, the results are also very similar across all years in the sample.

S1.2 Minimum wage and the hourly wage distributions in the DADS data

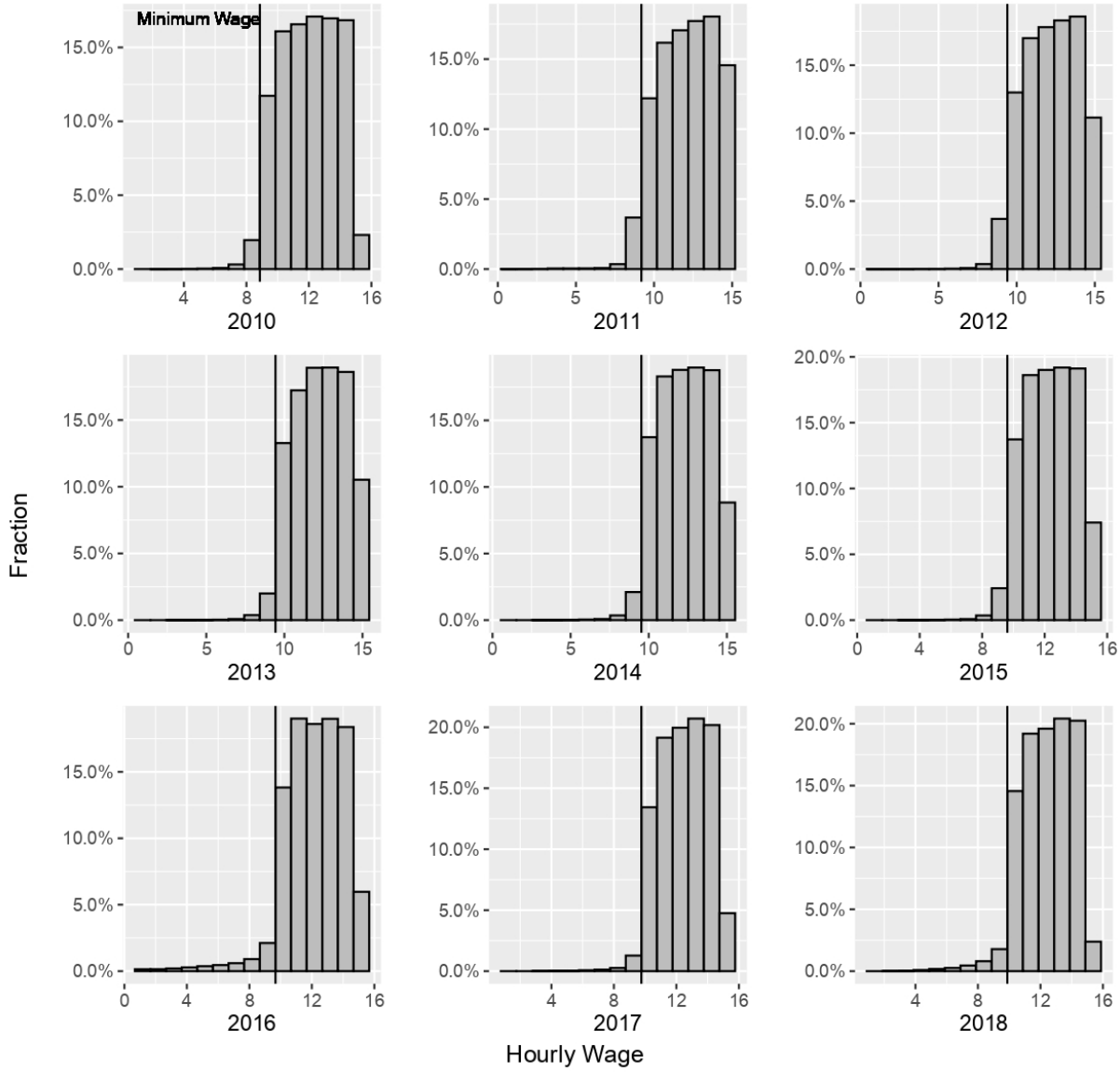
A straightforward way to capture the quality of the hourly wage data in our sample is to assess whether the distribution of hourly wages exhibits a peak at the minimum wage and how this peak varies across years following each annual minimum wage increase.[20] To investigate this issue, we report in Figure S1 the annual distribution of hourly wages for each year from 2010 to 2018 for workers paid less than 16 euros per hour. In each graph, a vertical bar indicates the corresponding hourly wage rate of the French minimum wage for that year.[21] Consistent with the hypothesis that the data are of good quality, the distribution of hourly wages exhibits a distinct peak at the minimum wage and this peak shifts annually following the minimum wage increases. In Table S3, we report the corresponding share of workers in the sample with hourly wages lower than the minimum wage. In most years, that share is below 1%.

[20] Since 2010, the French minimum wage has been indexed annually in January on the past yearly increase in the consumer price index and half of the real annual increase of a wage index published quarterly, the base hourly wage rate of blue-collar workers.

[21] We focus on years after 2010 as, before that year, the annual adjustment of the minimum wage occurred in July instead of January, and there were thus two different minimum wages in a single year. The minimum wage can also be updated during the year if the annual increase in CPI observed in the monthly series is superior to 2%, which only happened twice in December 2011 and in July 2012. For these two years, the graphs report the lowest value of the minimum wage.

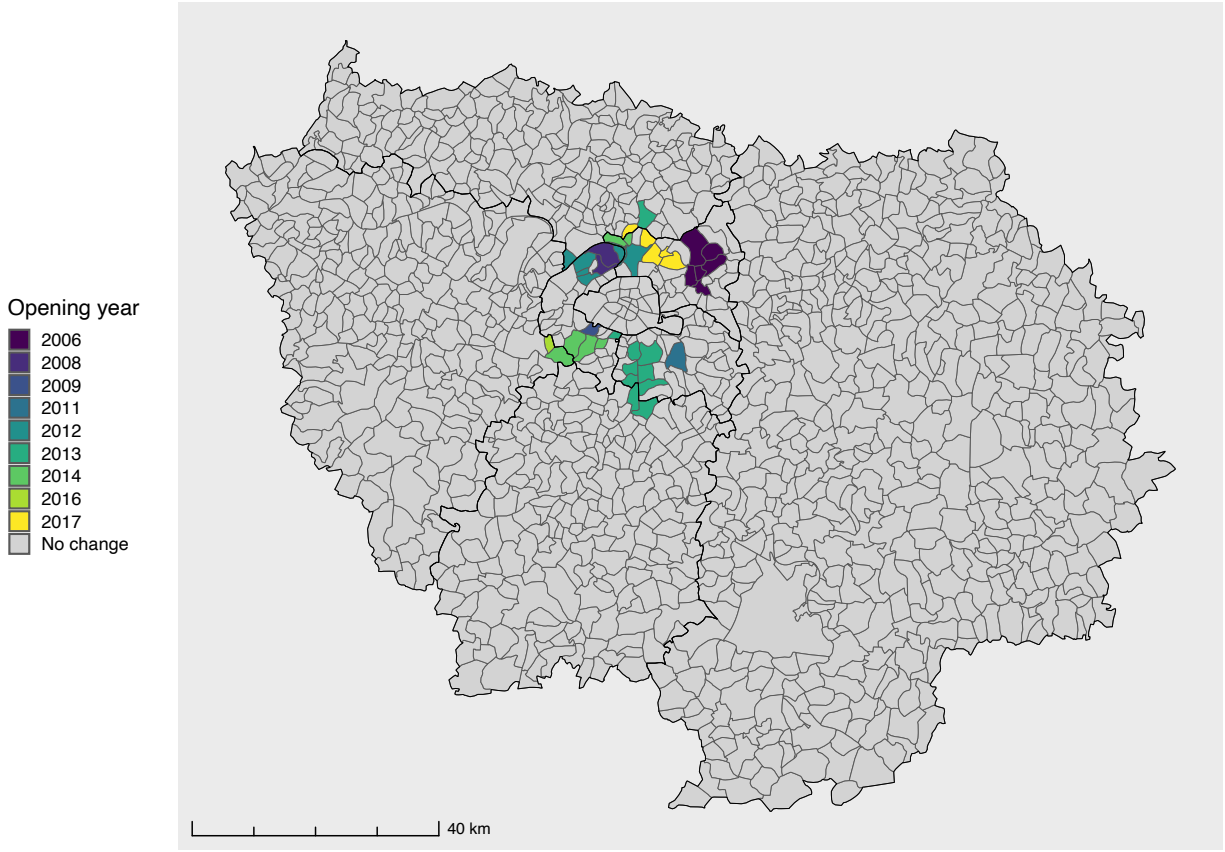
S2 Additional Figures

Figure S1: Hourly wage rate distributions and the national minimum wage, 2010–2018



Source: DADS. Note: Each figure represents the distribution of hourly wage rates in the indicated year for hourly wages below 16 euros. The vertical line denotes the value of the national minimum wage in the corresponding year.

Figure S2: Municipalities Affected by Transit Network Expansions



Sources: Maps from GEOFLA database; network changes compiled by the authors. *Notes:* The map shows, for each change in the transportation network documented in Table S1, the location of the affected municipalities and the corresponding year. When multiple openings occurred in the same municipality, only the year of the first opening is reported.

S3 Additional Tables

Table S1: Timeline of Mass Transit Extensions in the Paris Region, 2006–2017

Year Opened	Transit mode	Line Name	Number of New Stations	Station Span	Number of Municipalities Crossed	Municipalities Crossed
2006	Tramway	TRAM 4	10	Bondy – Aulnay-sous-Bois	6	Bondy, Villemomble, Les Pavillons-sous-Bois, Livry-Gargan, Sevran, Aulnay-sous-Bois
2008	Metro	METRO 13	2	Gabriel Péri – Les Courtilles	2	Asnières-sur-Seine, Gennevilliers
2009	Tramway	TRAM 2	5	Issy-Val-de-Seine – Porte de Versailles	1	Issy-les-Moulineaux
2011	Metro	METRO 8	1	Pointe du Lac	1	Créteil
2012	Metro	METRO 12	1	Porte de la Chapelle – Front Populaire	1	Saint-Denis
2012	Tramway	TRAM 1	10	Saint-Denis – Les Courtilles	3	L'Île-Saint-Denis, Villeneuve-la-Garenne, Gennevilliers
2012	Tramway	TRAM 2	7	La Défense – Pont de Bezons	4	Courbevoie, La Garenne-Colombes, Colombes, Bezons
2013	Metro	METRO 4	1	Mairie de Montrouge	1	Montrouge
2013	Tramway	TRAM 5	15	Marché de Saint-Denis – Garges-Sarcelles	2	Sarcelles
2013	Tramway	TRAM 7	17	Villejuif – Porte de l'Essonne	8	Villejuif, Vitry-sur-Seine, Chevilly-Larue, Thiais, Rungis, Paray-Vieille-Poste, Orly, Athis-Mons
2014	Tramway	TRAM 6	18	Châtillon-Montrouge – Robert Wagner	4	Châtillon, Clamart, Meudon, Vélizy-Villacoublay
2014	Tramway	TRAM 8	17	Saint-Denis Porte de Paris – Villetaneuse-Université / Epinay-Orgement	3	Saint-Denis, Villetaneuse, Épinay-sur-Seine
2017	Tramway	TRAM 11	6	Epinay-sur-Seine – Le Bourget	7	Epinay-sur-Seine, Montmagny, Villetaneuse, Saint-Denis, Stains, La Courneuve, Le Bourget, Drancy

Note: This table documents each metro station or tramway line opening in the Paris metro area between 2006 and 2017. For each opening, the table reports the number of newly created stations, the names of the first and last new stations, and the number and names of the municipalities crossed.

Table S2: Regression estimates of the change in log annual earnings on the change of log hours in the DADS

	Dependent variable: Change in log annual wages					
	(1)	(2)	(3)	(4)	(5)	(6)
Change in log annual hours	0.840	0.835	0.863	0.858	0.852	0.846
	(0.001)	(0.001)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Establishment fixed effects	No	Yes	No	Yes	No	Yes
Time period	2008-10	2008-10	2011-13	2011-13	2015-2018	2015-2018
N	6,711,123	6,711,123	6,785,682	6,785,682	11,132,942	11,132,942
Adj R2	0.75	0.76	0.76	0.77	0.74	0.75

Source: DADS data 2008-2018. The Table shows the estimates of regressions of the change in log annual earnings on change in the log annual hours using workers who remained in the same establishment. Each column reports a separate estimate performed on the indicated years. Columns 2, 4, and 6 report specifications including establishment fixed effects. Standard errors robust for clustering at the establishment level are reported in parenthesis.

Table S3: Are there many observations below the minimum wage?

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018
Share of workers with an hourly wagesbelow the minimum wage (%)	0.74	1.23	1.16	0.67	0.68	0.74	1.41	0.42	0.76

Source: DADS data 2008-2018. For each year, the table shows the share of workers with reported hourly wages below the minimum wage.

Table S4: Long-run effects

Outcome	A. Annual job separation probability									
Event year	-4	-3	-2	-1	0	0	1	2	3	4
ΔCommuting time	0.003	0.000	0.000	0.000	0.023***					
	(0.002)	(0.0001)	(0.003)	(0.000)	(0.004)					
ΔCommuting time >0						0.019***	0.017**	0.016	0.014	-0.002
						(0.006)	(0.008)	(0.008)	(0.008)	(0.009)
ΔCommuting time <0						0.029***	0.015	0.009	0.009	0.004
						(0.008)	(0.009)	(0.009)	(0.008)	(0.011)
N	123,928	173,971	256,493	330,645	403,957	403,957	126,002	110,259	93,191	70,290
R2	0.17	0.18	0.06	0.26	0.40	0.40	0.14	0.18	0.49	0.54
Sample composition	All workers in the establishment						Present at least 3 years before the relocation			
	B. Annual change in log hourly wages									
ΔCommuting time	0.000	0.000	0.001	0.002	0.003					
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)					
ΔCommuting time >0						0.007**	0.005	0.007**	-0.003	0.001
						(0.003)	(0.004)	(0.004)	(0.004)	(0.006)
ΔCommuting time <0						-0.003	-0.001	-0.003	0.000	-0.010
						(0.004)	(0.003)	(0.004)	(0.005)	(0.007)
N	116,143	168,823	247,339	242,194	122,841	122,841	103,024	89,215	67,604	48,966
R2	0.17	0.16	0.20	0.16	0.21	0.21	0.22	0.18	0.18	0.20
Sample composition	Present at least 3 years before the relocation									

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is the annual separation probability (Panel A) and the annual change in log hourly wage (Panel B) in the indicated event year. The explanatory variable is the change in commuting time by public transportation due to the relocation, measured in hours. Columns -4 to -1 show placebo regressions on outcomes observed one to four years before the relocation. Other columns report estimates for the relocation year up to four years post-relocation. The last five columns report separate estimates for commuting time increases and decreases. In Panel B, the sample is restricted to workers present at least three years before the relocation. All regressions include establishment by event year, occupation by event year, and fare zone changes fixed effects. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.

Table S5: Effects of relocation to the center on separation and wages by occupation groups

	Relocation type: Suburbs to Center					
	A. Dependent variable: Job separation probability in relocation year			B. Dependent variable: Log hourly wage change in relocation year relative to t = −3		
	All workers	Highly-paid	Low & Medium paid	All workers	Highly-paid	Low & Medium paid
ΔCommuting time	0.014	0.013	0.019	0.005	0.005	0.003
	(0.008)	(0.011)	(0.013)	(0.010)	(0.013)	(0.014)
N	23,844	15,726	8,118	12,496	8,001	4,495
R2	0.45	0.43	0.50	0.28	0.34	0.24

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is annual separation probability in the relocation year (Panel A) and the change in log hourly wage relative to event year −3 (Panel B). The explanatory variable is the change in commuting time by public transportation due to the relocation measured in hours, using only increases in Panel B. Within each panel, columns 2 and 3 show results for workers in low/medium- and highly paid occupations. The sample exclude commuting times affected by future network changes during the sample period. Only workers present for at least three years before the relocation and establishments observed over the six event years are included in the sample. All regressions include establishment by event year, occupation by event year, and fare zone changes fixed effects. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.

Table S6: Effects of commuting time on hours worked and change in place of residence

Event year	-2	-1	0	1	2
Outcome	A. Change in log hours worked per day				
ΔCommuting time by public transportation > 0	0.002	0.001	-0.004	0.002	0.002
	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
N	250,324	249,071	126,650	126,650	92,984
R2	0.13	0.13	0.15	0.17	0.17
Outcome	B. Probability to change residency (conditional on staying in the establishment in next period)				
ΔCommuting time by public transportation > 0	-0.001	0.001	-0.002	-0.002	-0.003
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
N	249,942	134,532	104,296	90,829	69,328
R2	0.14	0.14	0.61	0.21	0.13

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is the change in log hours per day in the indicated event year (Panel A) and the probability of changing residence (Panel B). The explanatory variable is the increase in commuting time by public transportation due to the relocation, measured in hours. Columns 1 and 2 display placebo regression for outcomes observed two and one year before the relocation. Other columns report estimates for the relocation year and one and two years post-relocation. Only workers present for at least three years before the relocation and establishments observed over the six event years are included in the sample. In Panel B, we only include workers remaining in the establishment in the event year. All regressions include establishment by event year, occupation by event year, and fare zone changes fixed effects. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.

Table S7: Testing for nonlinear effects

	(1)	(2)	(3)
Outcome	A. Job separation probability in relocation year		
ΔCommuting time by public transportation	0.022***	0.023***	
	(0.005)	(0.005)	
(ΔCommuting time by public transportation)^2		-0.004	
		(0.008)	
Δlog (Commuting time by public transportation)			0.015***
			(0.003)
N	243,584	243,584	243,584
R2	0.48	0.48	0.48
	B Log hourly wage change in relocation year relative to t = –3		
ΔCommuting time by public transportation >0	0.011***	0.007	
	(0.004)	(0.010)	
(ΔCommuting time by public transportation >0)^2		0.001	
		(0.005)	
Δlog (Commuting time by public transportation) >0			0.010***
			(0.003)
N	122,455	122,455	122,455
R2	0.22	0.22	0.22

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is annual separation probability in the relocation year (Panel A) and the change in log hourly wage relative to event year -3 (Panel B). The explanatory variables are based on the change in commuting time by public transportation due to the relocation, measured in hours, using only increases in Panel B. Column 2 includes are quadratic term of the commuting time change measure. Column 3 reports results using the change in log commuting time. Only workers present for at least three years before the relocation and establishments observed over the six event years are included in the sample. All regressions include establishment by event year, occupation by event year and fare zone changes fixed effects. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.

Table S8: Effects of workers' selection on wage estimates

Outcome	Log hourly wage change relative to event year t= −3				
Event year	-2	-1	0	1	2
Sample	Balanced sample using observed in the establishments over 6 years				
ΔCommuting time by public transportation > 0	0.001	0.005	0.008**	0.005	0.011**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)
N	76,734	76,734	76,734	76,734	76,734
R2	0.30	0.27	0.29	0.31	0.24

Source: DADS data 2003-2018. *Note:* The table presents regression results where the dependent variable is the change in log hourly wage in the indicated event year relative to event year −3. Only workers present continuously from at least three years before the relocation to three years after are included in the sample. The explanatory variable is the increase in commuting time by public transportation due to the relocation, measured in hours. Columns 1 and 2 display placebo regressions for outcomes observed two and one year before the relocation. Other columns report estimates for the relocation year and one and two years post-relocation. The sample is restricted to establishments observed over the six event years. All regressions include establishment by event year, occupation by event year, and fare zone changes fixed effects. Standard errors are clustered at the establishment by event year level. (*), (**) and (***) denote statistical significance at 10%, 5% and 1% level, respectively.