GRADO EN ECONOMÍA

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TRABAJO FIN DE GRADO

TÍTULO en Inglés
The commuter toll: a commuting cost and wage inequality analysis

TÍTULO en Español
El peaje del trayecto al trabajo: un análisis del costo del desplazamiento y la desigualdad salarial

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1. ABSTRACT / RESUMEN

The growth of cities and transportation infrastructure improvements have significantly altered commuting patterns in recent years. Understanding how much time workers spend commuting is crucial for grasping its impact on their quality of life and the extent at which it contributes to enlarge inequality in the labor market. This study provides a descriptive analysis of how commuting time affects workers in the Community of Madrid, depending on their income levels. This work introduces a new measure that combines workers' hourly wages with their daily commuting time. Presented findings suggest that workers living in lower-income geographical area bear a heavier economic burden from commuting time. Furthermore, it is found that commuting time exacerbates gender disparities more significantly among workers with Basic and Middle levels of education compared to those with higher education.

El crecimiento de las ciudades y las mejoras en la infraestructura de transporte han alterado significativamente los patrones de desplazamiento en los últimos años. Comprender cuánto tiempo pasan los trabajadores en sus desplazamientos es crucial para entender su impacto en su calidad de vida y en qué medida contribuye a aumentar la desigualdad en el mercado laboral. Este estudio proporciona un análisis descriptivo de cómo el tiempo de desplazamiento afecta a los trabajadores en la Comunidad de Madrid, según sus niveles de ingresos. Este trabajo introduce una nueva medida que combina el salario por hora de los trabajadores con el tiempo diario que dedican a desplazarse. Los hallazgos presentados sugieren que los trabajadores que viven en áreas geográficas de ingresos más bajos soportan una carga económica más pesada debido al tiempo que dedican a desplazarse. Además, se obtiene que el tiempo de desplazamiento agrava las disparidades de género de manera más significativa entre los trabajadores con niveles básicos y medios de educación en comparación con aquellos con educación superior.

2. INTRODUCTION

Inequality is an indispensable element in understanding the development of societies throughout history. In recent decades, partly due to a paradigm shift in global politics towards a more socially oriented approach that emphasizes the paternalistic role of the state, issues surrounding inequality have dominated political discourse. This renewed focus is aligned with a strong body of scientific evidence supporting a close correlation between high levels of inequality and a range of social issues, including increased crime rates (Kelly, 2000), deteriorating public health (Pickett & Wilkinson, 2015), and slower economic growth (Partridge, 1997). These links underscore the importance of addressing wage inequalities from a broad and multidimensional perspective.

Driven by the desire to understand inequality, economic research has yielded a vast literature, prompting the emergence of the concept of "inequality economics" as an area of growing focus. Building on the conception of wages as one of the primary drivers of inequality, numerous articles examine wage inequality in labor markets (Katz & Autor, 1999), (Van Reenen, 2010), (Acemoglu & Autor, 2011). As human capital theory posits, investments in skills and experience, leading to accumulated human capital, are rewarded differently in the market, resulting in wage disparities (Becker, 1964). This market driven wage inequality can be further examined through two main perspectives: supply side, which focuses on worker characteristics as the source of inequality (Moretti, 2013), (Juhn, Murphy, & Pierce, 1993), (Lemieux, 2006), and demand side, centered on hiring decisions by firms (Mueller, Ouimet, & Simintzi, 2017), (Song, Price, Guvenen, Bloom, & von Wachter, 2019). Is from a supply-side perspective when the study of commuting time disparities as a potential driver of wage inequality emerges.

On this matter, it is common to observe wage disparities in isolation, without considering other socio-economic factors that may be contributing to their exacerbation. This limited approach overlooks relevant aspects that could influence the already present wage inequalities. Among these factors, workers commuting time to work can be a contributor to widening existing wage gaps. In this regard, increasing interest in the role of commuting patterns in shaping worker decisions is evidenced by a growing body of economic research. At this point, a key distinction emerges between the perspectives of labor and urban economics (White, 1986). Labor economists, assuming fixed wages, view longer commutes as deserving of higher compensation. Conversely, urban economists, assuming fixed housing costs, suggest lower housing costs can offset longer commutes. As Mulalic, Van Ommeren, & Pilegaard (2014) point out, modelling commuting decisions requires assumptions about both labor and housing markets. In this context, it is crucial to conceptualize commuting time as a factor that may aggravate wage inequality since it generates disutility and incurs associated costs for workers (Stutzer & Frey, 2008). The negative effects of long commuting times have been shown to manifest in numerous ways, impacting various dimensions of commuter's lives. Concerning health, Chatterjee et al. (2020) find that longer commuting times are associated with lower subjective health levels and Künn-Nelen (2016) reveals that it leads to a higher rate of visits to healthcare practitioners. Similarly, Hansson, Mattisson, Björk,et al. (2011) concur on the adverse effects of long commuting time on health, particularly in relation to higher stress levels. Clark, Chatterjee, Martin, & Davis (2020) determine that an increase in the length of commuting time impacts negatively job satisfaction and the availability of leisure time, while also increase stress levels and worse mental health. However, Hansson, Mattisson, Björk, et al. (2011), Clark, Chatterjee, Martin, & Davis (2020) and Chatterjee et al. (2020) concur that the impact over job satisfaction levels vary significantly across different commuting transportation modes. In addition to the individual negative effects, longer commutes are associated to a higher CO_2 emissions rate, especially for the case of private vehicles (Cirilli & Veneri, 2014).

Although the negative effects of commuting time, commuters do not experience these effects equally. Rather, the impact of commuting time responds to individual-level characteristics such as gender, income or ethnicity. In this sense, most of the findings referring to commuting time disparities concern gender issue. According to Gordon, Kumar, & Richardson (1989), women tend to have shorter commutes than men, even after accounting for income, occupation, and marital status. This observed difference in commuting preferences aligns with the findings of Barbanchon, Rathelot, & Roulet (2021), which reveal that women place a higher value on shorter commutes and state that a significant portion of the persistent gender wage gap, amounting to 14%, can be attributed to this phenomenon. Parallel, Farré, Jofre-Monseny, & Torrecillas (2023) estimate that an increase of 10 minutes in commuting time leads to a 4.4% decrease in the likelihood of married women participating in the workforce. Furthermore, the article findings reveal an amplified effect for mothers with more children and originating from countries with stricter gender roles. Similarly, considering marital status, Black, Kolesnikova, & Taylor (2007) further reveals that married women's labor force participation, growth lagged behind the overall growth of their respective metropolitan areas.

Concerning racial differences in commuting patterns, McLafferty & Preston (2019) highlight those Black and Hispanic workers experience longer commutes than their white counterparts, being these disparities exacerbated for the case of Black women. Income disparities further explain variations in commute times between workers. High-income workers, with a better financial situation, might be more willing to tolerate longer commutes to secure their preferred living arrangements (Zhao, Lu, & de Roo, 2011). Conversely, Crawley (2014) show that lower-income workers report lower job satisfaction due to commuting, while this effect is not observed for higher-income workers. In addition, as stated by DeSalvo & Huq (2005), commuting mode choice model, workers with higher wages use faster transportation mode. Moreover, given that public transportation is often considered an inferior good, implying a negative relationship between income and consumption, it is reasonable to assume that a significant portion of those who utilize public transportation for their commute are individuals with limited financial means. This reliance on public transportation, which may involve longer routes, less frequent service, and unpredictable schedules, can be contributing to extend commuting times for these workers.

In line with this literature, the present study aims to understand the extent to which the disparity in commuting durations among workers exacerbates existing wage inequalities through salaries. To comprehend the magnitude of these inequalities and their impact on different wage strata, an indicator that allows for the comparison of the economic value of commuting times among workers within a descriptive framework is proposed. Based on the premise that the time workers spend commuting to work is part of their working day, this indicator aims to reflect the variation in each worker's hourly wage by considering this time as part of their working day. This approach allows us to quantify the differential impact of commuting time disparities on various worker groups based on their wage levels. To achieve this, microdata on worker commuting patterns in the Community of Madrid for 2018 will be combined with other data sources on salaries and population at various geographical levels.

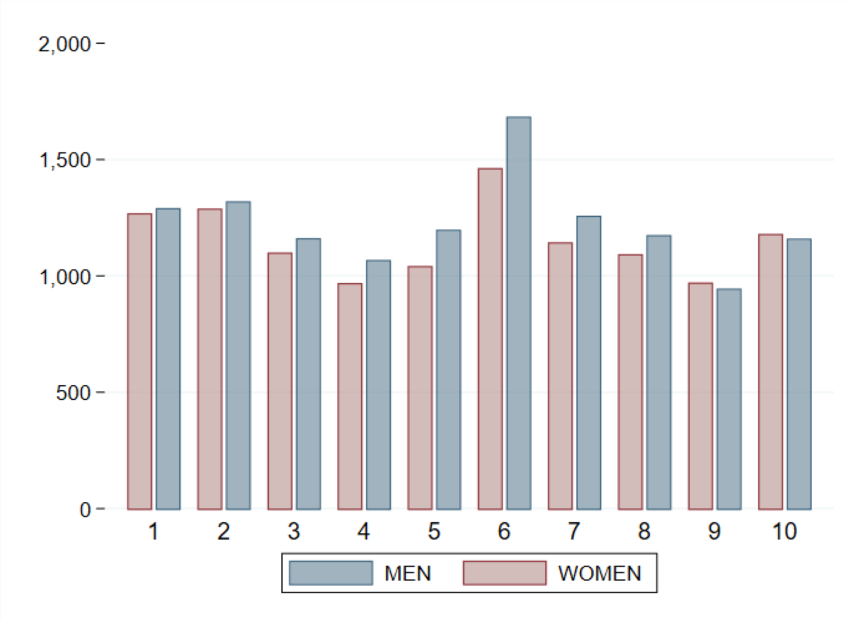
The structure of this paper is organized as follows. The data section reviews the data sources utilized in this study and outlines the data management procedures undertaken. Additionally, it includes a descriptive analysis of the sample data to characterize the individuals for whom the results will be obtained. In the results section, the developed indicator will be presented in detail, and the findings will be discussed in relation to the initial hypothesis. Finally, the conclusion section aims to provide a synthesis of the most relevant insights derived from the study.

3. DATA

3.1 MOBILITY HOUSEHOLD SURVEY

For the development of the present study, microdata from the Madrid Mobility Household Survey (EDM) 2018 has been used (Consorcio de Transportes de Madrid, 2018). This survey comprises three waves conducted between the years 2004 and 2018, with the last wave capturing information regarding the mobility on a working day of over 85,000 individuals residing in the Community of Madrid and their respective households. In addition to strictly mobility-related information of the respondents, it incorporates several socio-demographic variables enabling their characterization as required by this article. The survey data were predominantly collected via telephone interviews, with the remainder being the result of face-to-face surveys. The primary advantage of this data source over other alternatives for this purpose lies in the availability of microdata as well as the quantity of information related to respondents' mobility.

The sample has been restricted to individuals of working age who commute to work once or twice a day directly from their home or second home. As an exception, those workers who report making a maximum of one intermediate trip, either on their way to work at the beginning of the day or on their way home at the end of the workday to accompany a third person, were included. The decision to include these workers was made because it is highly probable that a large proportion of them make this intermediate stop to take or pick up their children from school. This commuting pattern is not only the most common in the sample (excluding those who go directly from home to work), but also, accepting the hypothesis that it is a journey to accompany a child to school, it is natural to assume that it is a task that inevitably affects commuting patterns to work, unlike other types of voluntary intermediate stops associated with leisure activities. Moreover, observations for which there is no information on entry or exit from work were excluded, as the remaining information was insufficient for the study. Given that the target population comprises the workforce of the Community of Madrid, the initial sample was restricted to inhabitants of working age who reside and work within this region. As this study focuses on commuting time to work, the sample was also limited to those reporting one commute from their residence to their workplace and the return trip. After applying all these filters, the final number of observations is 23,661. The sample is balanced in terms of gender and age, as can be appreciated in *Graph 3.1*, where workers per deciles of age are classified by their gender.



Graph 3.1 Graph of Workers by Gender and Age Decile. Elaborated from EDM data

The zoning employed in the EDM 2018 distinguishes between 1,259 transport zones delimited on the tiling defined by the Statistical Institute of the Community of Madrid (Instituto de Estadística de la Comunidad de Madrid, 2011). Furthermore, the delineation within the municipality of Madrid corresponds to that of its districts. More information concerning the survey is reported in the Madrid Transport Consortium web page[1]. For working with spatial information, QGIS software has been employed, being all the maps presented in the following lines elaborated with it.

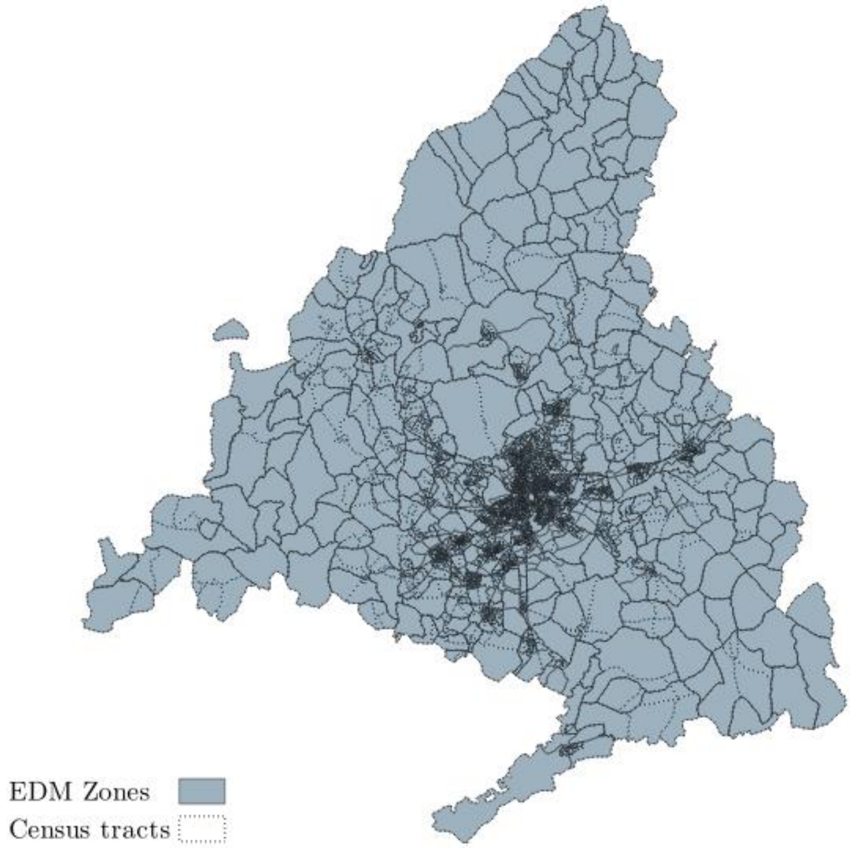
From this data, the methodology employed in this article is typical of a descriptive study of this nature. Based on this data and with the aim of testing the hypothesis that commuting times to work affect workers differently depending on their income, an indicator is developed to capture the variation in hourly wages experienced by each worker when commuting time is considered an extension of the workday. This approach allows for the evaluation of the impact of commuting time on different income quantiles.

3.2 INCOME IMPUTATION

Due to the absence of hourly wage data in the EDM dataset, gross income data for each specific zone has been imputed from the Household Income Distribution Atlas provided by the INE (Instituto Nacional de Estadística, 2018). Hourly wages for each worker have been calculated separately based on this imputed data. For this imputation, data on annual mean salary incomes per census tract for the year 2018 were used. However, it is important to clarify that the zoning system utilized by the EDM does not directly align with the geographical delineation of census tracts. This is because each zoning system is based on distinct criteria for territorial delineation. Therefore, a zone within the EDM does not necessarily represent a straightforward aggregation of multiple census tracts. Instead, any of the 1259 zones established by the EDM may encompass territories from various census tracts. To address this mismatch between zonings, the shapefiles corresponding to both have been combined, resulting in each EDM zone being a sum of intersections of census sections with the delimitations of the first. Graph 2.2 shows the result of the combination of shapefiles, with the dashed lines corresponding to the boundaries of the

[1] https://www.crtm.es/conocenos/planificacion-estudios-y-proyectos/encuesta-domiciliaria/edm2018.aspx

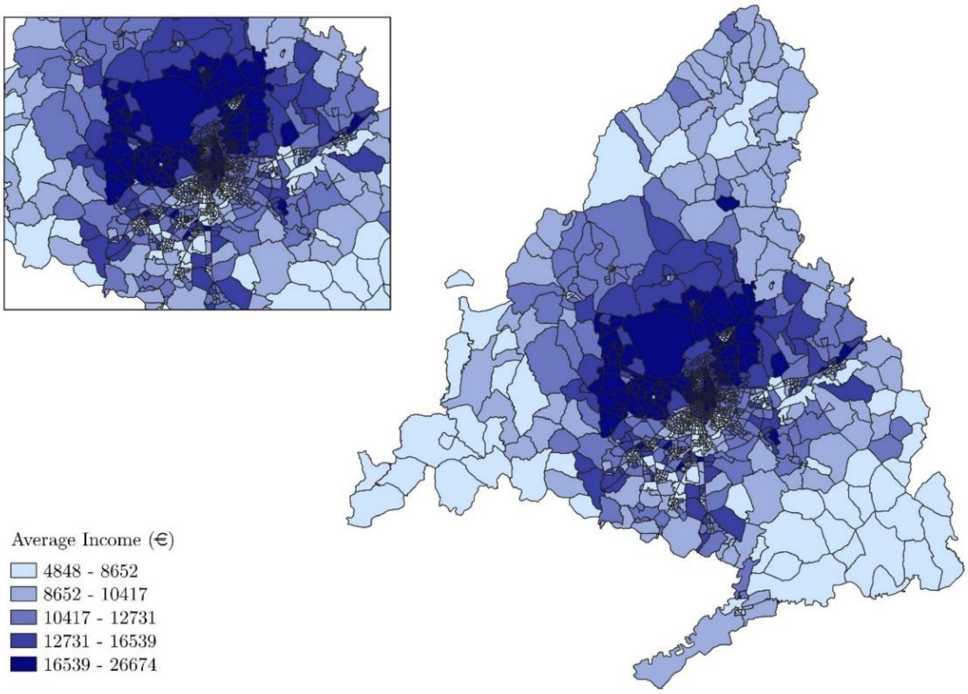
census sections and the solid lines to the boundaries of the EDM zones.
For the imputation of a single salary indicator for each EDM zone, a weighted mean salary has been computed. This is based on mean salary income per census section, employing the estimated population percentage of each section residing in a specific zone serving as the weighting factor. Population data at the census section level were also sourced from the Continuous Census Statistics provided by the INE (Instituto Nacional de Estadística, 2018.). For the population estimation it is assumed that this is evenly distributed within each section territory. Based on this assumption, the estimated population of each EDM zone can be obtained from the proportion of area of each census tract that falls within the area of every EDM zone. Using this assumption, the estimated population of each EDM zone can be derived by calculating the proportion of area within each census tract that intersects with the area of each EDM zone.



Graph 3.2 Zoning Intersections. Elaborated from EDM and INE Geographical Data

After adding the estimated population of each section within a specific zone, the weighted mean salary was calculated using the proportion of estimated inhabitants in each section as weights. As a result of this computation, the geographical distribution of mean zone wages is shown in Graph 3.3. The map evidences a clear clustering of the highest incomes in the central area of the Community of Madrid, with lower incomes in the outer perimeter, particularly in the southern area. When specifically examining the Madrid municipality, it becomes evident that heterogeneity exists, as the Northern districts exhibit higher incomes compared to their Southern counterparts. In addition to the evident geographical heterogeneity, the difference in average salary between areas at the tails of the distribution is considerable. In this regard, some areas in the municipalities of Alcalá de Henares or Torrejón de Ardoz have, according to the imputations made, average salaries around 5,000 euros per year, while certain areas in

Alcobendas or Pozuelo de Alarcón, exceed 26,000 euros. Given this heterogeneous distribution of wage incomes in the territory of the Community of Madrid, and considering that the majority of employment in the region is concentrated in the municipality of Madrid (Matas, Josep-Lluis, & R., 2010), it is reasonable to expect a sizable group of low-income workers who are compelled to commute from the outskirts to downtown Madrid for work given the lower cost of housing in many areas compared to the city center.



Graph 3.3 Mean Annual Income per Zone in Euros. Elaborated from INE data

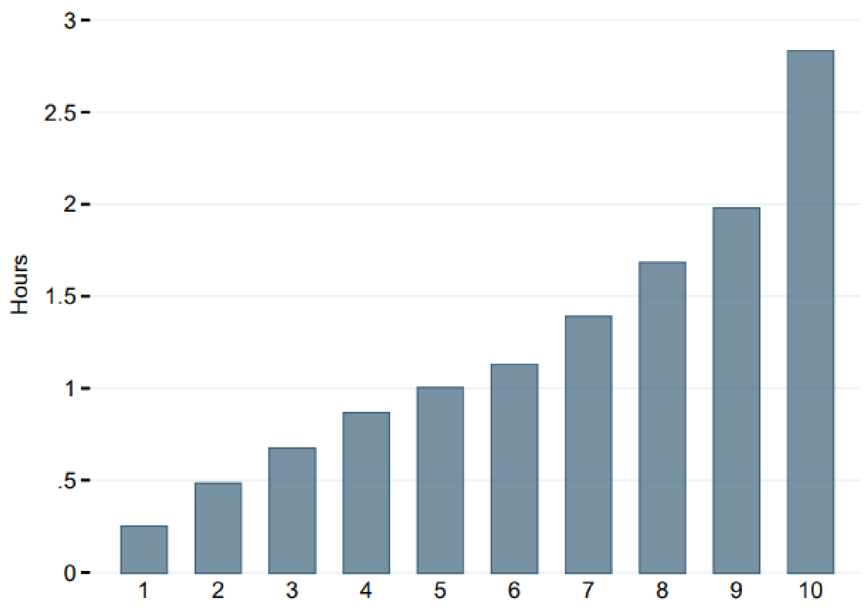
Once the mean wage income for each zone has been imputed to every individual attending to its residence location and the workday duration has been computed, hourly wages can be determined by dividing the daily salary by the number of hours worked in a day. Considering that the wage data represent annual earnings, it is needed to divide these earnings by the number of days worked per year. However, since the days worked for each observation are not available in the EDM, a standard work calendar of 250 days per year has been assumed. When calculating the hourly wage for an employee, considering commute time as part of the workday, the process remains the same, with the distinction that the total duration of daily commuting hours is added to the standard work hours.

4. HETEROGENITY ANALYSIS

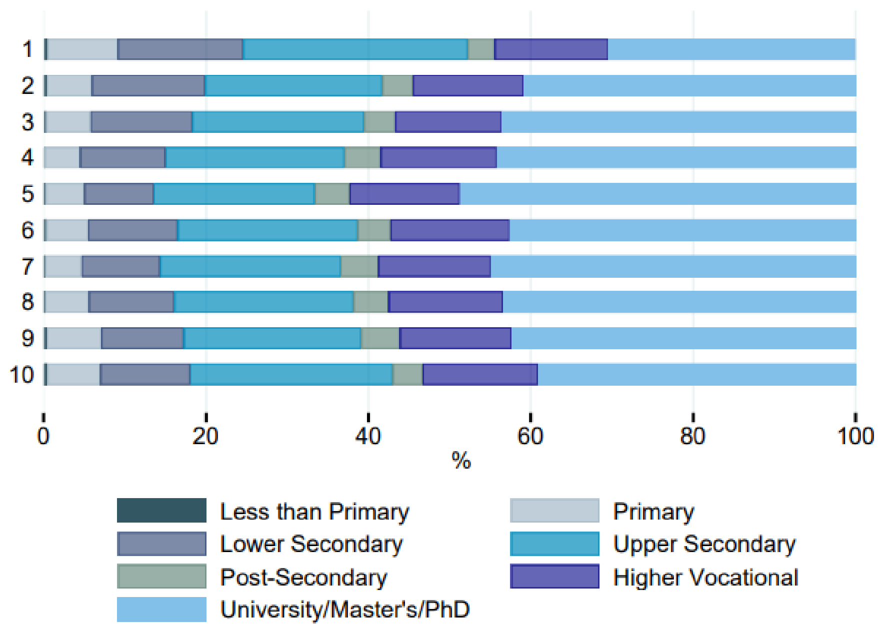
4.1 COMMUTING TIME

With the aim of calculating the total duration of commutes associated with work throughout the day for each worker, the departure and arrival times at various possible origin-destination combinations which meet the previously mentioned criteria, are considered. In this computation, hours are not rounded. For workers with split shifts, the commuting time between shifts is calculated excluding stops for accompaniment, which are only possible at the beginning and end of the workday.
Graph 4.1 displays the distribution of the variable representing the commuting time for each

worker across 10 quantiles. The height of each bar corresponds to the mean hours of commuting time for the workers in that particular quantile. This figure indicates a significant variability in the amount of time workers spend commuting to and from work throughout the day. While the mean commuting time is 1 hour and 12 minutes, workers in the lowest quantile spend less than 20 minutes per day commuting to work, whereas those in the highest quantile spend more than 3 hours. One interesting question to consider is whether there are significant differences in commuting time among workers based on their educational attainment. Exploring these differences can provide valuable insights into how education levels are related to travel routines. The Graph 4.2 categorizes workers into deciles of commuting time according to their highest level of education completed.

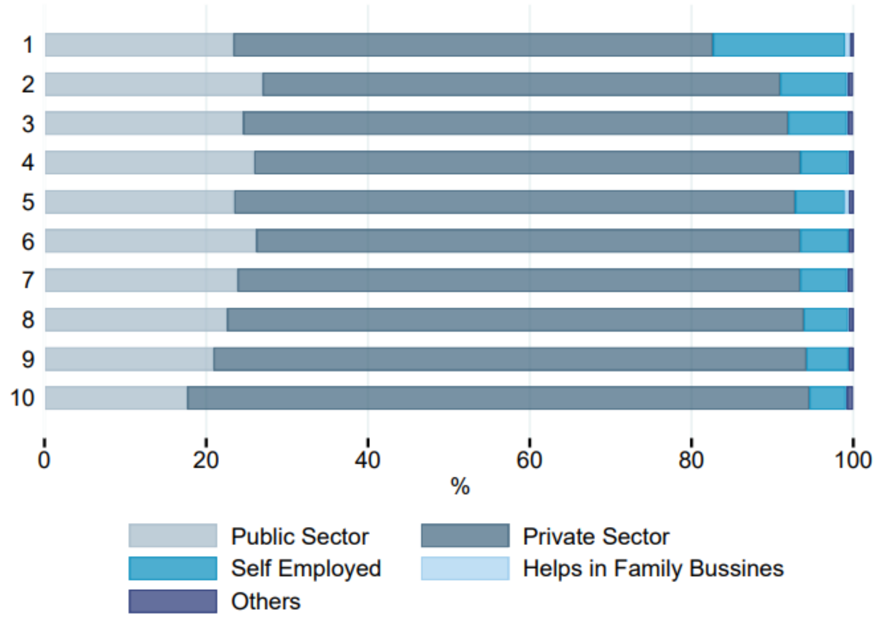


Graph 4.1 Mean Commuting Time by Decile. Elaborated from EDM Data

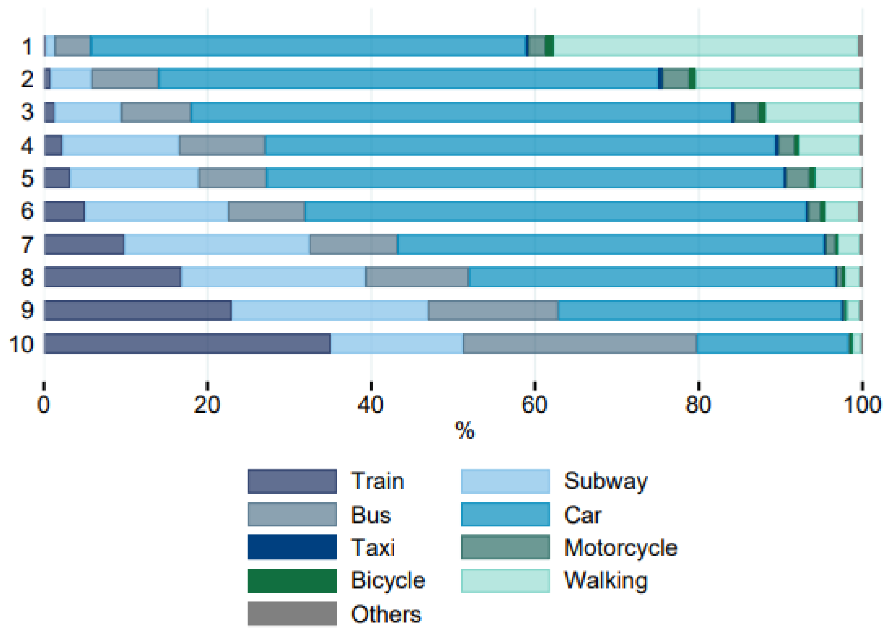


Graph 4.2 Level of Completed Studies by Decile of Commuting Time. Elaborated from EDM Data

This analysis highlights disparities in the commuting times of workers with varying educational backgrounds, which are especially notable for the lower deciles of the distribution. It is observed that workers with higher education levels are less represented in the lower deciles of commuting time, with their presence increasing up to the fifth decile. Notably, the fifth decile serves as a turning point, from which the proportion of workers with lower educational levels slightly increases at the expense of those with university degrees, decreasing to as low as 10%.
Regarding the professional activity of the workers, the observed differences between deciles of commuting time are not as pronounced as in the previous figure. However, Graph 4.3 highlights that the percentage of self-employed individuals or entrepreneurs in the first decile of commuting time is significantly higher than in the rest. Additionally, the proportion of public sector workers decreases as commuting time increases, albeit very moderately.



Graph 4.3 Professional Activity by Decile of Commuting Time. Elaborated from EDM Data



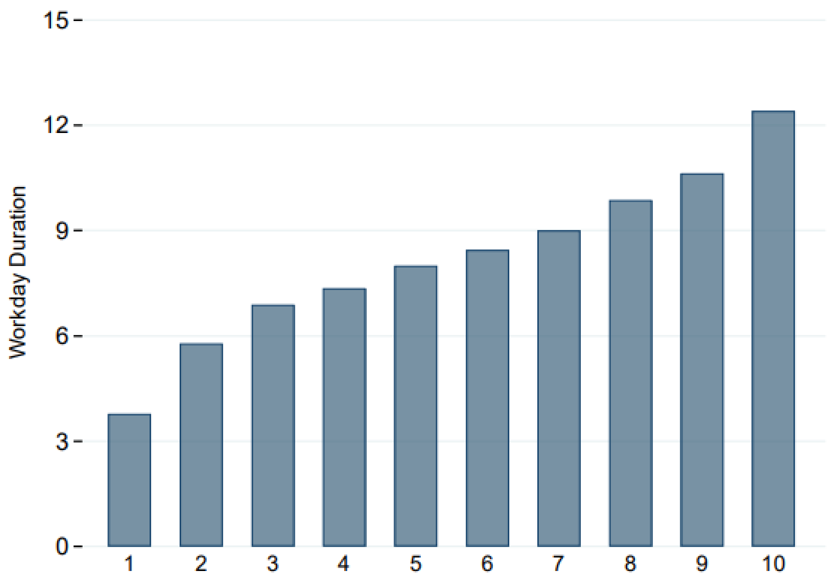
Graph 4.4 Modality of Commute by Commuting Time Decile}

As introduced in previous sections, not only the time invested in commuting to work but also the mode of transportation is seen to have a significant impact over subjective wellbeing. Attending to the mode of transport employed by deciles of commuting time, Graph 4.4 shows how it varies depending on the length of the commuting time. It should be noted that given the possibility of each worker to employ different transportation modes in each of it's commuting along the day, the transportation mode employed for the first commute is the one represented in the figure.

This analysis reveals significant variations in the modes of transportation used by workers based on the duration of their commute to work. One of the most notable trends is the marked difference in car usage among workers depending on their commuting time decile: while car usage varies moderately between other groups, a drastic decrease is observed in the decile with the longest commute time, diminishing from 35% in the ninth decile to 19% in the last. Concurrently, the proportion of workers walking to work decreases by almost half in the second decile compared to the first. Overall, there is an increase in the use of public transportation as commuting duration increases, with the eighth decile being the point at which the majority of workers opt for this mode of transportation. While the presented data do not allow for causal relationships to be established, they offer valuable insights for hypothesis formulation. Moreover, these data may provide insights into the potential relationship between the transportation mode used for commuting and income level.

4.2 WORKDAY DURATION

On the purpose of comparing the distributions of hourly wages with and without commuting time included in the workday, two variables are essential: the length of the working day and the total duration of commutes to work along the day.
Firstly, the duration of the workday is calculated from the hourly differences between arrival and departure times at the workplace. Since the arrival time may not necessarily coincide with the contracted starting hour (similarly for the departure time), the resulting number of hours has been rounded to the nearest whole number, as it is more realistic to assume a standard work schedule based on whole hours rather than fractional hours. This rounding is crucial for the accurate computation of the hourly wage discussed later.

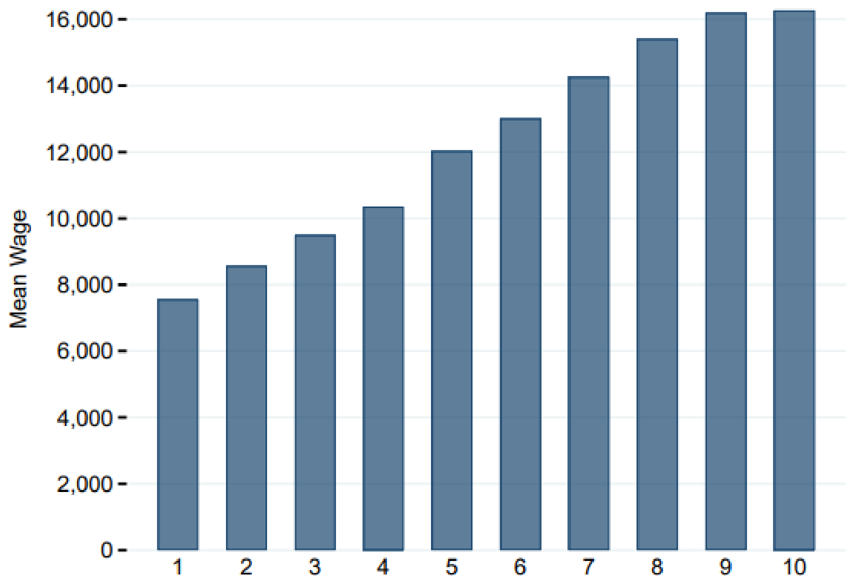


Graph 4.5 Mean Workday Duration per Decile. Elaborated from EDM Data

Graph 4.5 shows the distribution of this variable by deciles, highlighting significant differences in the duration of the workday. The mean workday duration for the sample is 8 hours and 3 minutes.

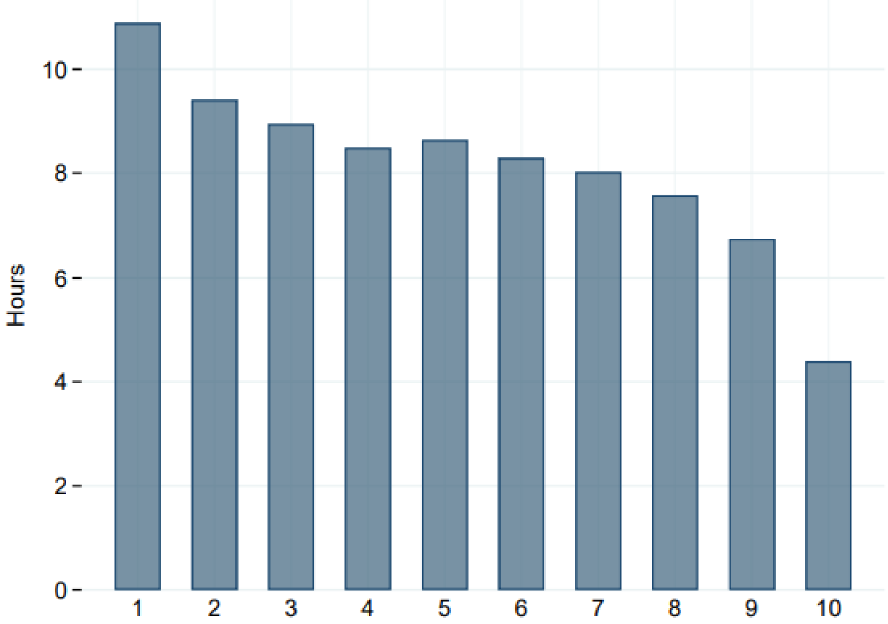
4.3 HETEROGENEITY ACROSS INCOME DECILES

Concerning the variable that captures the mean annual earnings of their respective residential zone, the distribution of these incomes across deciles is depicted in Graph 4.6. While variability exists among deciles, it is notably more moderate for the upper deciles. It is worth noting that the mean imputed income for the upper decile exceeds more than double that of the first decile.



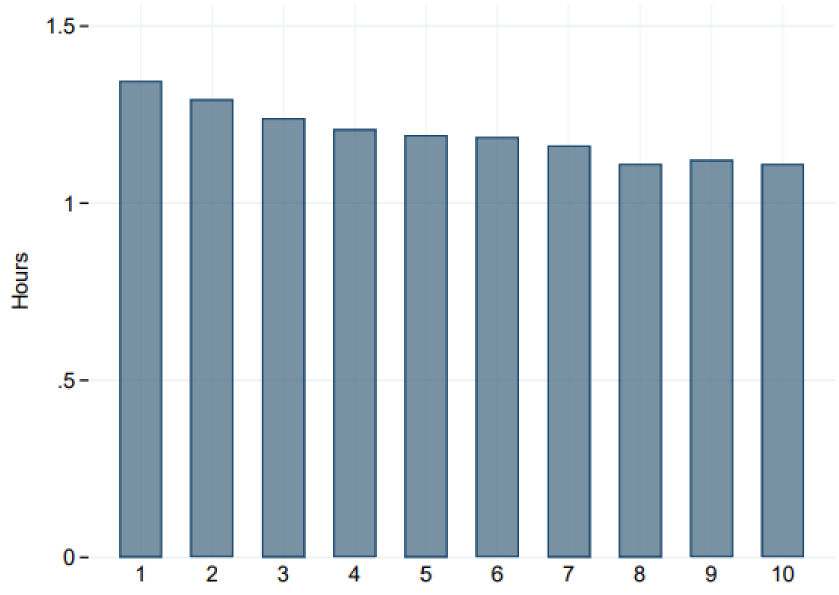
Graph 4.6 Mean Income by Decile. Elaborated from EDM Data

Additionally, Graph 4.7 shows a negative correlation between mean zone income and workday duration. The observed downward trend suggests a significant decrease in mean workday duration, with this decrease being most pronounced at the upper tail of the distribution, particularly between the highest and ninth deciles. It should be noted that, on average, individuals in high-income geographic areas report working less than half the hours of those in the bottom decile of the salary distribution, yet they earn more than double (specifically 109% if the tails deciles are compared). Thus, while one might anticipate observing a more substantial effect of commuting time among lower-income zones residents, it is crucial to acknowledge that individuals residing in high-income geographical zones also work fewer hours in average. At this respect, Graph 4.9 shows that in the tail deciles of the income distribution, the self-employed or business owners have a greater weight. However, it is to be expected that these represent different profiles of self-employed individuals. In any case, the presented results are not significantly altered by excluding this group of workers.



Graph 4.7 Workday Duration for Each Wage Decile. Elaborated from EDM Data

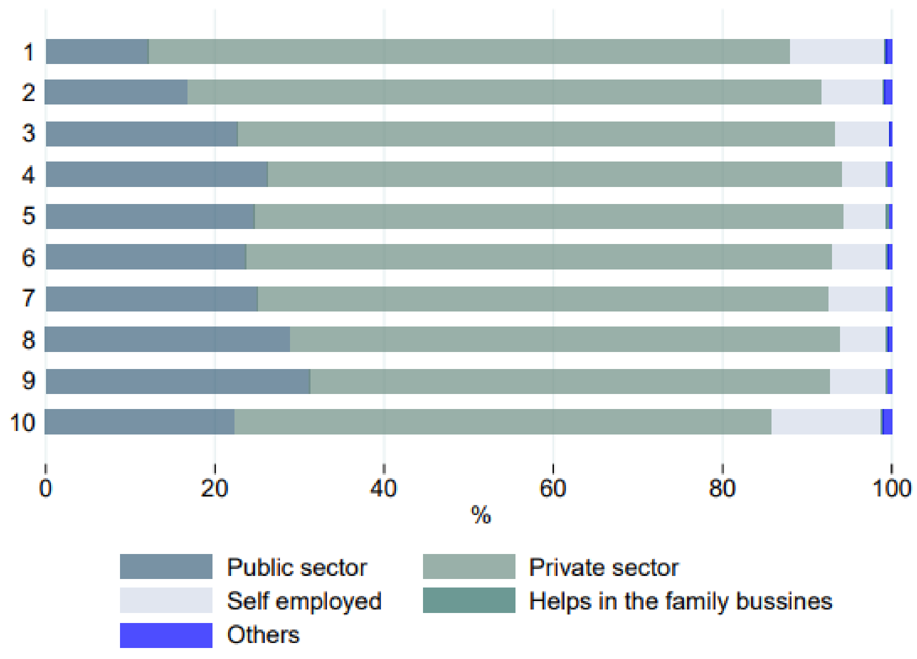
Furthermore, the distribution of mean commuting time across income deciles exhibits a different pattern compared to the aforementioned variable affecting the indicator since it displays a more homogeneous distribution as evidenced in Graph 4.8. This suggests that commuting time is relatively evenly distributed among different income groups. Even though, a clear inverse relationship exists between wages and commuting time, consistent with the argument put forth by DeSalvo & Huq (2005) that higher-wage workers tend to utilize faster modes of transportation.



Graph 4.8 Commuting Time for Each Wage Decile. Elaborated from EDM Data

The main conclusion drawn from this graph is that, although higher-income workers tend to spend less time, on average, commuting to work, the variations observed in this variable are smaller than those in wages or workday duration.

Regarding the distribution of workers according to their professional occupation in each income decile, Graph 4.9 shows how workers in the private sector and self-employed or entrepreneurs have a greater presence in the income deciles located at the tails of the distribution, to the detriment of public sector workers. It is noted that both those who collaborate in family businesses and workers in the sample engaged in other classifications of alternative labor activities represent a residual percentage.



Graph 4.9 Distribution of Occupational Activities by Income Decile. Elaborated from EDM Data

5. RESULTS

This section presents the impact of commuting cost of hourly wages. To this end, two distributions of hourly wages have been obtained. The first corresponds to hourly wages calculated conventionally, based on actual working hours. Additionally, the distribution of hourly wages has been derived by incorporating time spent daily on commuting to and from work as part of the workday. By comparing these individual-level data, it becomes possible to assign an economic value to each individuals commuting time based on its residential zone mean earnings. Through this indicator, it can be examined the extent to which the duration of commutes affects various wage profiles differently. In other words, it can be assessed whether there is a clear correlation between the economic value of commuting time for individuals and their income level.

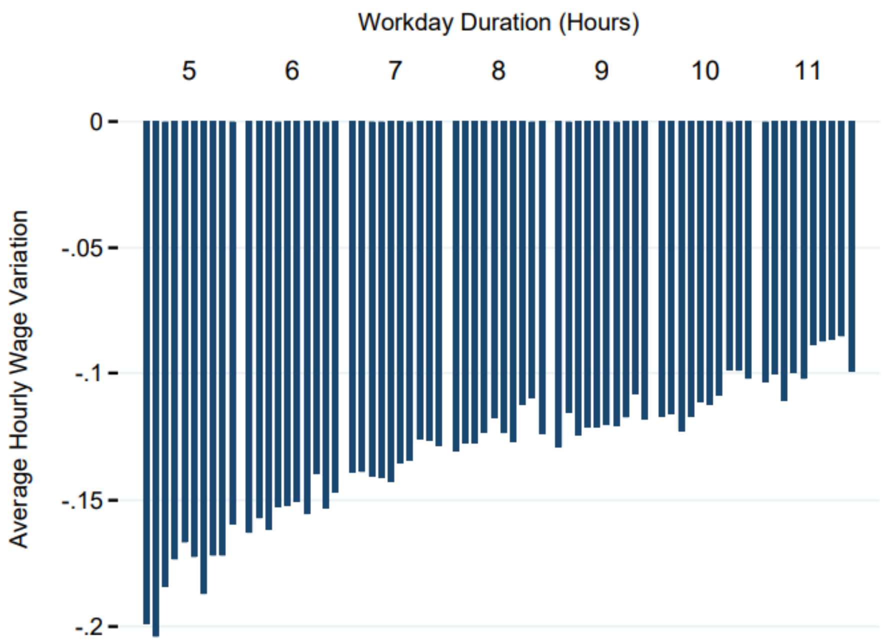
As previously mentioned, this study employs the variation in hourly wages, considering commuting time as part of the workday duration, as an indicator for assessing the impact of commuting time on wage inequality. Before proceeding with the results, it is important to note that directly comparing salary variations based on the proposed indicator among workers with different work schedules would not be feasible. This is because the indicator primarily relies on hourly wages as the key variable for studying variation, incorporating commuting time into the duration of the workday. Since individual salary data is unavailable, all workers residing in the same area have the same total salary, but not necessarily the same hourly wage. Hourly wages would depend on the estimated duration of the workday, implying that for workers with identical salary levels, the hourly wage would be higher for those with shorter workdays. Comparing variation in these hourly wages would result in distorted outcomes that would affect the interpretation of the results. Therefore, the alternative would be to compare salary variation stemming from commuting time conditioning on duration of the workday. Thus, the only sources of difference would be commuting time or the salary assigned to each worker. It is important to note that for this comparison to be feasible, there must be groups of workers with different workday durations sufficiently large to ensure the representativeness of the results being compared. In this regard, the sample includes more than 1,000 observations for each workday duration ranging from 5 to 11 hours, inclusive. Thus, 85% of the workers in the sample have a workday duration between 5 and 11 hours. Additionally, the mean standard deviation of wages across groups of workers, segmented by workday duration, exceeds 4,000.

Workday Duration	N	Mean	sd
5	1355	-0.1766274	0.097739
6	2087	-0.1537831	0.0810182
7	3738	-0.1348733	0.0721901
8	4480	-0.1219984	0.0631831
9	3570	-0.1212009	0.0630024
10	3166	-0.1117922	0.0571591
11	1867	-0.0962855	0.0497716
Total	20263	-0.1271959	0.0705685

Table 5.1 Workday Duration Statistics

In Graph 5.1, the variation in hourly wages is shown when including commuting time as part of the workday for each income decile. The income deciles correspond to the distribution of the "wages" variable conditioned on the workday duration. As expected, there is a decrease in the impact of commuting time as the workday duration increases. This result is intuitive, as there is no perfect correlation between the workday duration and the commuting duration. Therefore, it makes sense to assume that as the workday lengthens, the commuting time has relatively less weight compared to the total workday duration.

It is important to consider the unequal distribution of the number of observations in each of these groups presented in Table 5.1, where these data are reflected as well as the mean variation of the indicator for each group and the standard deviation. The table confirms that the differences in the mean effect of commuting time among workers with different workday durations are greater for those groups situated at the tails of the distribution shown in the graph. In other words, the average impact of commuting time on workers with 5 and 11-hour workdays deviates more from the mean than that of groups of workers more centered in the hours of work distribution.



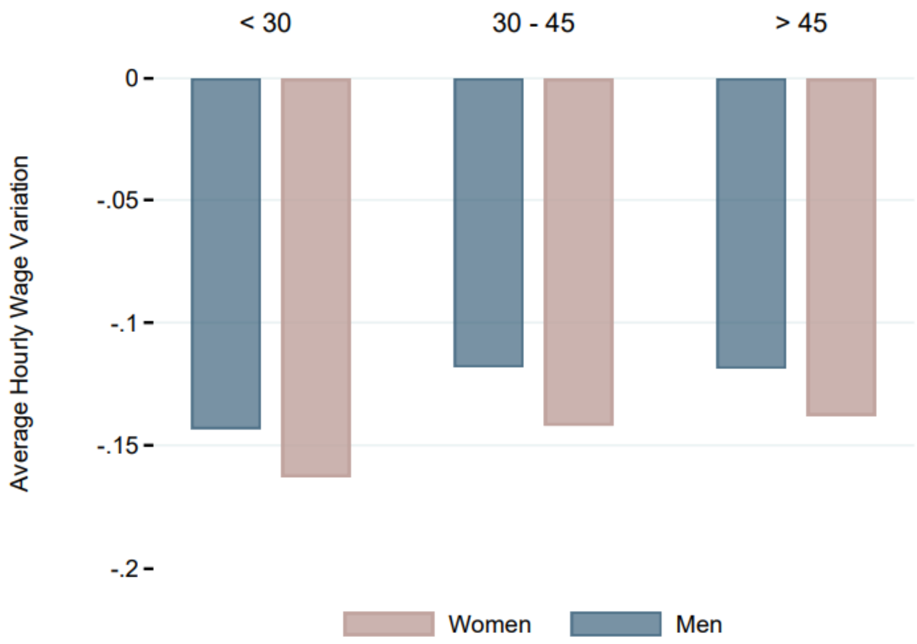
Graph 5.1 Hourly Wage Variation by Workday Duration and Wage Decile. Elaborated from EDM Data

Nevertheless, the main concern of the present work is to assess the economic impact of commuting time based on the proposed indicator. In this sense, it can be observed how including the commuting time to and from job within the hours of work, affects income deciles unevenly regardless of the workday duration. In other words, this graph indicates that lower-income workers are simultaneously those most affected by commuting times. Analyzing each group of workers depicted in Graph 5.1, a negative correlation between the economic implications of commuting time and workers' wages it observed, with wage deciles arranged from lowest to highest. According to this analysis, the most pronounced impact resulting from incorporating commuting time into the workday is associated with the second income decile for the group of workers with a 5-hour workday, while the least impact would be for the ninth decile of workers with an 11-hour workday. Thus, according to the proposed indicator, the hourly wage would exhibit variations ranging from 8.32% to 20.53%. Nevertheless, it is important to note that the effect of commuting time, as measured by this indicator, does not consistently decrease as worker income rises; rather, it exhibits fluctuations.

By examining the results presented in the preceding graphs collectively, it is evident that the values of the indicator for different groups of workers depend particularly on the extent to which commuting durations contribute to the total hours worked, as well as on the wage level. In other words, despite higher-income workers working fewer hours on average and their commuting times not differing significantly from those of lower income deciles, they are less affected by commuting time according to the indicator because, although commuting time has a significant impact on this group compared to the length of their workday, the wage differential offsets the extent to which the proposed indicator penalizes shorter workdays.

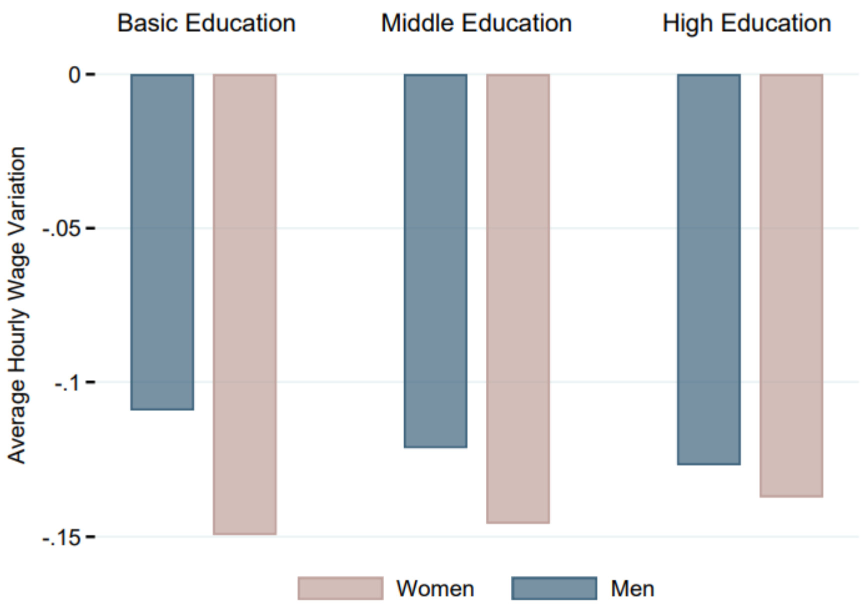
To elaborate on this finding, it is crucial to consider the economic rationale behind transportation choices. As income levels rise, individuals gain greater flexibility in their transportation decisions. They can opt for more expensive and time-efficient modes of transportation, such as private vehicles or express public transit options. This preference for faster travel options, in turn, may contribute to shorter commuting times for higher income individuals. In contrast, workers with lower incomes may face more constraints in their transportation choices. Limited financial resources may restrict their ability to afford private vehicles or premium public transit services. Consequently, they may rely on less expensive but more time-consuming modes of transportation

In addition to grouping workers by the income level of the area they reside in; other comparative analyses are essential to understand how the effects of commuting are distributed among workers according to various demographic characteristics. In this regard, Graph 5.2 shows hourly wage variations for three age groups, disaggregated by gender. These results indicate that, according to the indicator, younger workers are the most affected by commuting time, although the differences compared to those over 45 years old do not exceed 5%. Furthermore, women, across all age groups, are the most penalized by the duration of commuting, with the difference compared to men remaining constant across the three age groups considered.



Graph 5.2 Hourly Wage Variation by Age Group and Gender. Elaborated from EDM Data

Additionally, a comparative analysis by highest education level attained has also been performed. The education categories used in Graph 4.2 have been distributed into three groups: the basic education group includes workers with an educational level below “Upper secondary”, and the higher education group includes those with an equivalent of a university degree, Master’s degree, or PhD. The remaining workers have been included in the middle education group.



Graph 5.3 Hourly Wage Variation by Education Level and Gender. Elaborated from EDM Data

The results of this analysis are shown in Graph 5.3 and present opposing trends between men and women. That is, while the indicator shows a greater effect for more educated men, in the case of women, the effect of commuting time on wages decreases as the education level increases. Again, women are the most disadvantaged by commuting time, although in this case, the differences decrease as the education level of both men and women increases. Additionally, from this graph, it can be inferred that considering commuting costs as a potential source of labor market inequalities exacerbates gender differences in the labor market between the group with higher education and the rest.

6. CONCLUSION

This analysis deepens our understanding of the relationship between commuting time and wage disparities, shedding light on potential socioeconomic implications and addressing a gap in the existing academic literature. The results reveal that the negative effect of commuting time, measured as a decrease in hourly wages when incorporating com muting time into the workday, is unevenly distributed among different groups of workers. Specifically, there is heterogeneity both among workers with different workday durations and among workers with varying income levels. For the former classification, the results align with expectations given the nature of the indicator: the impact of commuting time is greater for those with shorter workdays. Conversely, concerning income deciles in the wage distribution, a negative relationship is observed, with lower-wage workers bearing the greatest economic burden of commuting to work. In terms of gender, notable differences have been found, especially when considering the level of education. Specifically, commuting exacerbates gender differences in the labor market more significantly among workers with Basic and Middle levels of education. Conversely, age has not been found to have a similar effect on gender disparities.
However, it's important to acknowledge the limitations of this analysis. Foremost among these is the necessity to impute the area's median salary to each worker due to the absence of such information in the EDM dataset. This lack of precision compared to an analysis based on administrative data with detailed individual characteristics is a notable constraint. Additionally, working with estimated workday durations may introduce deviations from actual durations. Furthermore, calculating hourly wages based on the average incomes of each area without

adjusting for individual workday durations limits the scope of analysis. Thus, it’s imperative to compare the effects of commuting time for groups of workers with the same estimated workday duration, excluding those groups with insufficient observations.

7. REFERENCES

1. Acemoglu, D., & Autor, D. (2011). Chapter 12 - skills, tasks and technologies: Implications for employment and earnings. In D. Card & O. Ashenfelter (Eds.), *Handbook of labor economics* (Vol. 4, pp. 1043–1171). Elsevier.

2. Barbanchon, T. L., Rathelot, R., & Roulet, A. (2021, February). Gender differences in job search: Trading off commute against wage. *The Quarterly Journal of Economics, 136*(1), 381–426.

3. Becker, G. S. (1964). Human capital: A theoretical and empirical analysis with special reference to education. University of Chicago Press.

4. Black, D. A., Kolesnikova, N. A., & Taylor, L. J. (2007). The labor supply of married women: Why does it differ across U.S. cities? *Labor: Supply & Demand*.

5. Chatterjee, K., Chng, S., Clark, B., Davis, A., De Vos, J., Ettema, D., & Reardon, L. (2020). Commuting and wellbeing: a critical overview of the literature with implications for policy and future research. *Transport Reviews, 40*(1), 5–34.

6. Cirilli, A., & Veneri, P. (2014). Spatial structure and carbon dioxide (CO2) emissions due to commuting: An analysis of Italian urban areas. *Regional Studies, 48*(12), 1993–2005.

7. Clark, B., Chatterjee, K., Martin, A., & Davis, A. (2020). How commuting affects subjective wellbeing. Transportation, 47*, 2777–2805.

8. Consorcio de Transportes de Madrid. (2018). *Encuesta domiciliaria de movilidad de la Comunidad de Madrid*. Retrieved from https://www.crtm.es/conocenos/planificacion-estudios-y-proyectos/encuesta-domiciliaria/edm2018/?lang=en

9. Crawley, A. (2014). The relationship between commuting time and workers' utility. *Applied Economics Letters, 21*(18), 1273–1276.

10. DeSalvo, J. S., & Huq, M. (2005). Mode choice, commuting cost, and urban household behavior. *Journal of Regional Science, 45*(3), 493–517.

11. Farré, L., Jofre-Monseny, J., & Torrecillas, J. (2023, July). Commuting time and the gender gap in labor market participation. *Journal of Economic Geography, 23*(4), 847–870.

12. Gordon, P., Kumar, A., & Richardson, H. W. (1989). Gender differences in metropolitan travel behaviour. *Regional Studies, 23*(6), 499–510.

13. Hansson, E., Mattisson, K., Björk, J., et al. (2011). Relationship between commuting and health outcomes in a cross-sectional population survey in southern Sweden. *BMC Public Health, 11*, 834.

14. Instituto de Estadística de la Comunidad de Madrid. (2011). *Callejero*. Retrieved from https://www.madrid.org/iestadis/fijas/estructu/general/territorio/planocalle.htm

15. Instituto Nacional de Estadística. (2018). *Estadística del padrón continuo*. Retrieved from https://ine.es/dyngs/INEbase/es/operacion.htm?c=EstadisticaC&cid=1254736177012&menu=resultados&secc=1254736195461&idp=1254734710990

16. Instituto Nacional de Estadística. (2018). *Atlas de distribución de renta de los hogares*. Retrieved from https://ine.es/dyngs/INEbase/operacion.htm?c=EstadisticaC&cid=1254736177088&menu=resultados&idp=1254735976608

17. Juhn, C., Murphy, K., & Pierce, B. (1993). Wage inequality and the rise in returns to skill. *Journal of Political Economy, 101*(3), 410–442.

18. Katz, L. F., & Autor, D. H. (1999). Changes in the wage structure and earnings inequality. *Handbook of Labor Economics, 3A*, 1463–1555.

19. Kelly, M. (2000). Inequality and crime. *The Review of Economics and Statistics, 82*(4), 530–539.

20. Künn-Nelen, A. (2016). Does commuting affect health? *Health Economics, 25*(8), 984–1004.

21. Lemieux, T. (2006). Postsecondary education and increasing wage inequality. *American Economic Review, 96*(2), 195–199.

22. Matas, A., Josep-Lluis, R., & R., J.-L. (2010). Job accessibility and female employment probability: The cases of Barcelona and Madrid. *Urban Studies, 47*(4), 699–923.

23. McLafferty, S., & Preston, V. (2019). Who has long commutes to low-wage jobs? Gender, race, and access to work in the New York region. *Urban Geography, 40*(9), 1270–1290.

24. Moretti, E. (2013). Real wage inequality. *American Economic Journal: Applied Economics, 5*(1), 65–103.

25. Mueller, H. M., Ouimet, P. P., & Simintzi, E. (2017). Wage inequality and firm growth. *American Economic Review, 107*(5), 379–383.

26. Mulalic, I., Van Ommeren, J. N., & Pilegaard, N. (2014). Wages and commuting: Quasi-natural experiments' evidence from firms that relocate. *The Economic Journal, 124*(579), 1086–1105.

27. Partridge, M. D. (1997). Is inequality harmful for growth? Comment. *The American Economic Review, 87*(5), 1019–1032.

28. Pickett, K. E., & Wilkinson, R. G. (2015). Income inequality and health: A causal review. *Social Science & Medicine, 128*, 316–326. doi: 10.1016/j.socscimed.2014.12.031

29. Song, J., Price, D. J., Guvenen, F., Bloom, N., & von Wachter, T. (2019, February). Firming up inequality. *The Quarterly Journal of Economics, 134*(1), 1–50.

30. Stutzer, A., & Frey, B. S. (2008). Stress that doesn't pay: The commuting paradox. *The Scandinavian Journal of Economics, 110*(2), 339–366.

31. Van Reenen, J. (2010). The race between education and technology. *The Economic Journal, 120*(548), F505–F510.

32. White, M. J. (1986). Sex differences in urban commuting patterns. *The American Economic Review, 76*(2), 368–372.

33. Zhao, P., Lu, B., & de Roo, G. (2011). The impact of urban growth on commuting patterns in a restructuring city: Evidence from Beijing. *Papers in Regional Science, *90*(4), 735–755.*