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Abstract:

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Keywords: Commuting; floor-area-ratio (FAR); lockdown; COVID-19; Recife

JEL Codes: C38, C21, R11, R12.

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ABSTRACT

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RESUMO

Este estudo trata da contaminação pela COVID-19 e sua relação com a intensidade construtiva da cidade, o tempo de deslocamento das pessoas ao trabalho e a dinâmica do mercado de trabalho durante o período de lockdown. Utilizam-se microdados de trabalhadores formais, disponíveis para a cidade do Recife, ajustando um modelo de probabilidade de contração da doença. Descobrimos relações positivas e significativas entre essas características urbanas e o aumento do contágio, controlando uma série de fatores como vizinhança, características dos indivíduos, comorbidades, ocupações e atividades econômicas. Nossos resultados mostram que uma maior distância ao emprego aumenta a probabilidade de infecção. O mesmo acontece com a intensidade construtiva, indicando que moradias em áreas mais densas, como apartamentos em prédios, condomínios e favelas, aumentam as chances de contrair a doença. Também observa-se que trabalhadores formais, com ensino superior completo, têm menos chances de contágio, enquanto que profissionais de saúde, na linha de frente do combate à doença, têm maior risco. Em geral, o lockdown foi eficaz na redução do contágio por reduzir a mobilidade das pessoas, no período.

Palavras-chave: Commuting; floor-area-ratio (FAR); lockdown; COVID-19; Recife.
Jel codes: C38, C21, R11 and R12.

1. Introduction

The COVID-19 virus originated in China and rapidly spread to virtually every other country worldwide, escalating into a major pandemic (Who, 2020). As observed, this virus posed particularly high risks, given the potential progression of infected individuals to conditions such as pneumonia and other pulmonary problems, explaining its estimated mortality rate of up to 3% (Who, 2020; Wang et al., 2020; Bourdin et al., 2021). Considering that the survival of the virus is contingent on local climatic conditions, and its transmission requires some level of interaction or public exposure, variations in contagion rates are expected across different urban spaces.

Indeed, studies examining the risks of COVID-19 transmission have affirmed the significance of local spatial specifics in explaining spatial variance in contagion rates. Paez et al. (2021), focusing on the Spanish case, demonstrated that areas with higher temperatures and greater humidity exhibit lower contagion rates. Meanwhile, Cerqua and Letta (2022), and Carvalho et al. (2021), in the Italian and Portuguese contexts, respectively, indicated that locales specialized in service activities, demanding increased in-person interaction, were more affected by the pandemic. For the United Kingdom, Mutambudzi et al. (2021) highlighted a higher risk of severe conditions in essential sector workers. In China, the contagion risk appears to persist more in sectors such as petroleum, energy, gas, coal mining, and petrochemicals (SI et al., 2021). Concerning the United States, Desmet and Wacziarg (2021) suggested that the most pronounced effects of the COVID-19 pandemic were observed in poorer urban centers with lower educational levels.

Even more significant are the variations in these rates among individuals within cities. Despite being subject to similar climatic conditions, productive specialization, or individual characteristics (such as age and education), significant variations in COVID-19 contagion rates can be observed within cities. The knowledge of intra-urban factors responsible for the different virus dissemination rates, however, remains limited. In one of the few studies on this matter, analyzing the case of New York, Glaeser, Gorback, and Redding (2022) associated a 10% reduction in urban mobility with a 0.2-point decrease in COVID-19 contamination cases. Similarly, considering the case of Germany, Mitze and Kosfeld (2022) linked longer commuting distances to a 20% increase in virus spread. In turn, Rosenthal, Strange, and Urrego (2021), and Liu and Su (2021), documented the relative devaluation of more central and denser places, supposedly at higher risk of virus contagion, within American cities due to the COVID-19 pandemic.

This latter set of works suggests that characteristics of the urban structure of cities are associated with the different contamination levels observed within them. Using data from workers in the City of Recife, this study aims to analyze the importance of these characteristics for the spread of COVID-19. More specifically, two potential channels of COVID-19 contagion associated with urban features are investigated: differences in daily commuting and residential densities between the individuals' residential locations in the city. The working hypothesis is that longer daily commuting times may lead to a higher risk of virus exposure, an effect that would be potentiated with the use of public transportation. Regarding the place of residence, areas with higher residential density tend to favor greater interaction among people, whether in common private spaces such as elevators or in public spaces in the vicinity.

The availability of data for the City of Recife allows for exploring significant variance regarding the determinants of COVID-19 contagion chances (given its geography and urban heterogeneities). On the one hand, the city presents one of the longest daily commuting times for workers (Pero and Stefanelli, 2015), and as recently indicated by Lima and Silveira Neto (2019), it undergoes a process of constructive and population density, taking the form of a strong trend towards the verticalization of homes. On the other hand, its high income inequality and marked pattern of residential segregation by income (Oliveira and Silveira Neto, 2016) pose empirical challenges, given that the effects of urban and personal characteristics on contamination chances may be confounded.

The empirical strategy adopted addresses this challenge. First, a unique and comprehensive database regarding residents who underwent testing for contamination detection in the city was utilized, obtained from the government of the state of Pernambuco. In addition to personal characteristics, this information base allows the identification of individuals' domicile locations and their personal and locational features. Worker data available in the RAIS/MTE database was aggregated with this set of information, enabling the identification of individuals' workplace locations. With this information in hand, a binary variable indicating COVID-19 contamination or not (dependent variable) and the two variables of interest (distance from residence to workplace and constructive intensity or Floor Area Ratio of the individual's plot) were constructed.

To control endogeneity among variables, stemming from the simultaneity between the dependent variable and the independent variables of interest, the instrumental variables method is employed. For the extension of the individual's commuting, as in Duarte (2020), paths along the imperial tracks to the city's CBD4 are utilized. These tracks traversed the City of Recife, constructed for the transportation of sugar and cotton production to the port, shaping the current road pattern of the city. Regarding the constructive intensity of residents' plots, the apartment density of the 2000 census tract is used (obtained from Demographic Census data). These instruments are strongly associated with the variables of interest and, at the same time, do not seem to directly affect the chance of contagion through mechanisms other than those represented by the two variables.

In addition to this introduction, the article is structured into five more sections. Section 2 presents information and data on COVID-19 in the city of Recife, considering the urban context and the local job market. Section 3 introduces and discusses the adopted empirical strategy and the used database. Sections four and five present, respectively, the main research results and the results of heterogeneities and robustness tests. Finally, in section six, the study's conclusions are presented.

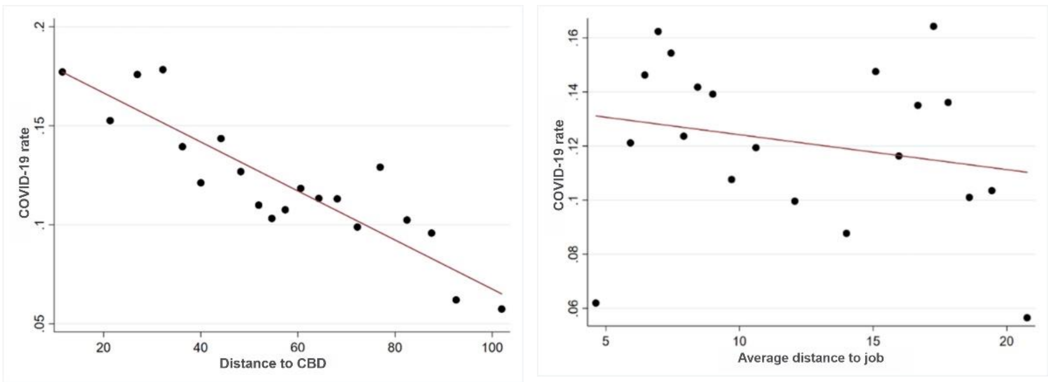
2. Recife, its Urban Structure, and COVID-19 Contagion

Founded on March 12, 1537, the former village of Recife, now the City of Recife, is one of the country's main and oldest urban centers and the current capital of the state of Pernambuco. Originating as a port city, this capital is typically a city with monocentric characteristics, with its Central Business District (CBD) concentrating approximately 26% of the total employment in the Metropolitan Region of Recife (MRR), comprised of fourteen municipalities, of which it is the core municipality.

Today, with around 1.5 million inhabitants, the city is also the ninth most populous city in the country and the fourth most densely populated Brazilian capital.

The advanced age, even for cities, poses challenges. Alongside the limited attention to public transportation expansion, the previous and old occupation of urban plots in times of limited dissemination of individual transportation modes such as cars, and the city's urban structure heavily centered on its sole CBD, seem to be behind the pronounced deterioration of its urban mobility in recent years. Among all metropolitan regions in the country, for example, the MRR experienced the highest growth in commuting time from home to work between 2003 and 2013 (Barbosa and Silveira Neto, 2017; Duarte, 2020).

Consistent with the city's monocentric profile, which therefore exhibits higher employment and demographic density near its CBD, Figure 3(a) below, based on census tracts of the city and utilizing survey data (discussed later), presents a clearly negative relationship between distance to the CBD and the COVID-19 contagion rate. In other words, given the strong concentration of employment and families in the more central regions of the city, it is not surprising to find the highest chances of virus contagion in these areas. On the other hand, the relationship presented in Figure 3(b) between the average distance to employment and the COVID-19 contagion rate is much weaker, suggesting that, contrary to the lower density of peripheral regions (farther from formal employment), the longer commuting of people in more peripheral census tracts may favor a higher chance of virus contagion. The figure also makes evident the presence of high contagion rates for people residing in locations with greater distances to employment.



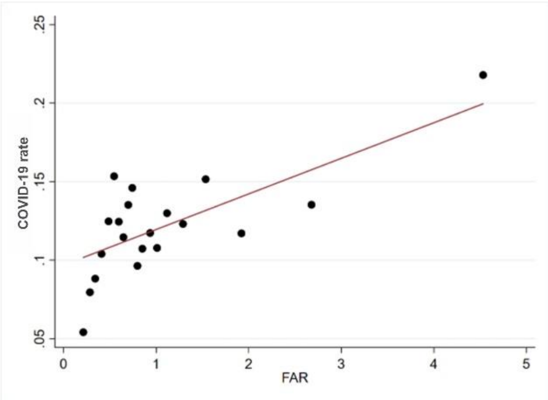
(a) Distance to CBD

(b) Average distance to job

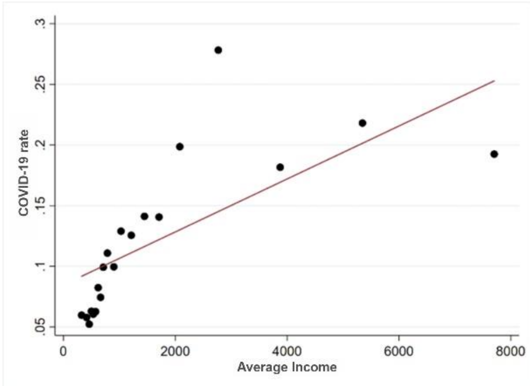
Source: Author's own elaboration.

Figure 1 – COVID-19 contagion rate and its correlation with daily commuting by census tract in the city of Recife.

However, the monocentric pattern also conditions its constructive pattern in different locations of the city. As a consequence of higher urban land valuation, buildings that use urban space more intensively (i.e., have a higher FAR) tend to appear near jobs and typical city amenities, such as rivers, beaches, parks, and ZEIS (Rodrigues, Silveira Neto and Miranda, 2019). Given the association between higher density and the chance of virus contagion, it is not surprising to observe the positive relationship between the FAR of census tracts and the chances of COVID-19 contagion presented in Figure 2(a) below. This relationship suggests that areas with a greater presence of buildings, condominiums, and more densely inhabited areas, such as favelas, may have a higher chance of COVID-19 contagion.



(a*) FAR*

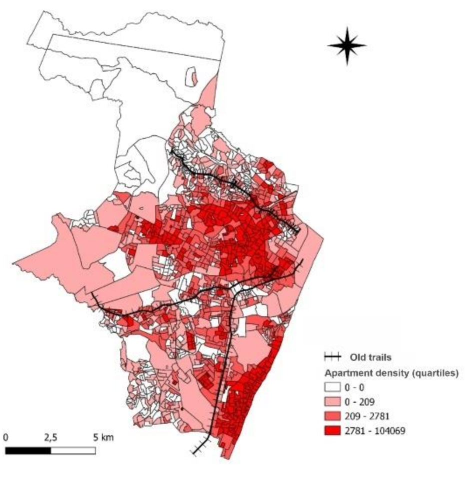


(b) Average Income

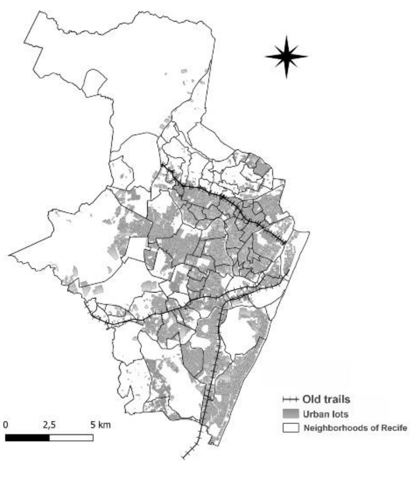
Source: Author's own elaboration.

Figure 2 – COVID-19 contagion rate and its correlation with the FAR and average income by census tract.

The relationships between longer commuting, higher constructive density, and the chances of COVID-19 contagion suggested by the presented figures can obviously mask influences from factors associated with both urban characteristics and virus contagion. For example, Figure 2(b) exemplifies such possibilities from the relationship between the income of sectors and their virus contamination rate. As higher-income families also tend to live in more verticalized places, which are generally closer to the CBD, any association (positive or negative) between income and the chance of contamination potentially makes the association between constructive intensity captured by the FAR and the chance of COVID-19 contagion spurious. The next section outlines the strategy used in the study to address these (and other) challenges.



(a) Urban lots and ancient imperial railway tracks



(b) Apartment densities per census tract

Source: Author's own elaboration.
Figure 3 - Ancient train tracks and apartment densities by census tract

3. Empirical Strategy

3.1 Econometric Specification

The empirical exercise proposed in this research seeks to test the hypotheses that the worker's longer daily commuting from home to the workplace and the residential constructive intensity positively affected the probability of their COVID-19 contagion during the SARS-COV2 epidemic in the city of Recife. To do so, the research employs econometric models to estimate the causal influences of these variables on the mentioned probability, considering formal labor market workers in the city in the year 2020. Formally, the following relationship is specified:

$$CVD_{ijkt} = \beta_0 + \beta_1 Dist_{ij} + \beta_2 FAR_i + X_{ijkt}\beta_3 + F_{ijkt}\beta_4 + \sigma_t + \varepsilon_{ijkt}$$

Where: CVD_{ijkt} is a binary variable equal to 1 if individual i, belonging to firm j in industry k, contracted COVID-19 in month t of the year 2020; zero otherwise. The explanatory variables are: distance to employment ($Dist_{ij}$), the constructive intensity of land use associated with the residence or *floor-area-ratio* (FAR_i), Xijk represents the socioeconomic characteristics of individual i working in industry k, the variables F_{jkt} correspond to the characteristics of firm j and industry k to which the individual belongs, (σ_t) corresponds to a fixed month effect, and ϵ_{ijkt} represents the error term.

In this specification, the two coefficients of interest are β_1 and β_2, which capture the influences of the variables distance to employment ($Dist_{ij}$) and the constructive intensity of the residence ($FARi$) on the chance of COVID-19 contagion. In both cases, positive effects are expected. That is, an increase in the commuting distance to work and exposure to the public over longer distances is expected to increase the risk of transmission for that individual, as well as for housing where the constructive intensity is higher. The distance variable is measured from the georeferencing of two geographic points: the location of the individual's residence and the location of the firm where they work. As discussed later, this construction was possible through the merge of two different databases. The second variable of interest, the floor-area-ratio (FAR_i), which captures the constructive intensity where the individual resides, is measured by the ratio of the square footage of the built area divided by the lot area (BRUECKNER, 2011); more formally, its value is obtained as follows:

$$FAR_i = \frac{arc_i + (arp_i x\, n)}{arl_i}$$

Where: arc_i is the common area, arp_i is the private area, n is the number of lots, and arl_i is the lot area.

Various reasons make obtaining causal effects of these variables on the chance of COVID-19 contagion quite challenging using conventional strategies (e.g., OLS or traditional non-linear models with probit or logit). Fundamentally, there is a significant set of observable and possibly unobservable factors that may be associated with the location of individuals' residence/work and the type of housing, simultaneously affecting the chances of COVID-19 contagion. To summarize the difficulties with more obvious examples, sorting based on the location of residence (or work) and type of residence (or occupation) by families based on income, education, or unobservable preferences would make coefficient estimates less credible (biased), as these factors also appear to affect the chances of COVID-19 contagion. The investigation addresses this challenge essentially in two ways.

First, it makes use of a considerable set of control variables that potentially affect the chance of a worker being infected by the virus at the individual, neighborhood, and firm levels. Specifically, in the first case, personal characteristics are considered (age, gender, race, comorbidities), levels of education, and income from work; in the second case, indicators of urban infrastructure services at the level of census tracts (2010) are considered (access to water, sanitation, and population density); finally, in the case of firms, categories of economic activities, firm size, and worker occupation categories are considered. Table 1 presents descriptive statistics for these variables.

In addition, since influences associated with unobserved factors may still compromise the estimates, the research uses instrumental variables (IV) for the two variables of interest (commuting distance and constructive intensity).

For the construction of an IV for commuting distance, the research follows a strategy similar to that applied by Haddad and Barufi (2017) and Duarte (2020) and uses the imperial railway tracks built in the city of Recife in the second half of the 19th century, no longer in operation. The railways were implemented in the city almost pioneeringly in Brazil and were intended for the export of sugar and cotton production to the port of Recife. The Recife and São Francisco Railway, the first English railway and the second implemented in Brazil, was inaugurated in 1858, connecting Recife to Cabo, covering a distance of 31.5 km. From there, other railways emerged that greatly facilitated the connection between the interior and the coast of the state (Cardoso and Albuquerque, 2020; Duarte, 2020). In 1881 and 1885, with the same economic purpose, the Recife to Limoeiro Railway and the Recife to Caruaru Railway were inaugurated, respectively (later called the Central Railway of Pernambuco). As shown in Figure 3(a) below, the old tracks associated with the three railway lines followed the orientation of the port area, departing from Recife to the east in southwest, northwest, and west directions. With the growth and urban spread, the old train tracks no longer function, but given the relief conditions of the city and its flooded sites, they facilitated the implementation of important city roads, such as the current Avenida Norte and Caxangá, and surface metro lines that became major connecting veins from the suburbs to the center.

As it is a city with essentially monocentric structure (Rodrigues, Silveira Neto and Miranda, 2019) and given the historical importance of railways in the formation of the city, the old tracks of the three imperial railways were used to construct an IV for the current commuting distance of individuals. This instrument precisely corresponds to the distance between residences and the current CBD of the city (Marco Zero) through the old tracks (Figure 3(a)). Note that, given the city's structure around its main center (CBD) and the use of the old tracks as paths for the implementation of part of the current roads, such IV tends to be clearly associated with the current commuting distance of the city's workers. Furthermore, as they are completely ignored by the current residents and firms of the city (except through the influence of current roads) when making their location decisions, it is also expected to be an exogenous instrument.

Regarding the FAR, the instrumental variable is constructed based on the apartment density of the census tract to which the FAR lot belongs in the city of Recife in the year 2000. To obtain this instrument, data on apartment density by census tract for the year 2000 were collected. Figure 3(b) below presents a framework of apartment density (quartiles) by census tract in the city of Recife for the year 2000. Note that the validity of this instrument is based on two fundamental conjectures. First, the idea that the city's urban structure retains a certain temporal rigidity, and therefore, the degree of constructive density of intra-urban locations is strongly related to its past. In this sense, it is expected that the current FAR related to a resident's residence in the city is clearly associated with the constructive density of the census tract of its location about 20 years ago, that is, a relevant instrument is expected here. On the other hand, this period of time is sufficiently long for the situation of the census tract to reflect factors associated with current decisions of residents and builders. That is, here too, the expectation is that the instrument is truly exogenous to current market conditions.

3.2 Data

The research uses different sources of information that are connected by identifying workers in different databases. Most of the information about the sample individuals, essentially personal and family characteristics, and information about COVID-19 test results in the year 2020, comes from official databases of the State Department of Health of Pernambuco. Note that this database provides two essential pieces of information for the research: information that allows identifying individuals in other databases used (by CPF) and their precise information about the location of residence (residential address). The individual from this first database is thus identified in the microdata of the Annual Social Information Report (RAIS), from which information about the labor market, including firm addresses and thus the workplace of these individuals, is extracted. Finally, with the identification of the residential location, it is also possible to obtain information about their neighborhoods from the census tracts of the 2010 Demographic Census.

Although it could be argued that the sample used may not be representative of the city's population since the State Health Department database may not include the entire city population tested for COVID-19, this apparent limitation is mitigated by the fact that in the city, the vast majority of people resorted to public instances for COVID-19 testing. It would also be possible to point out a certain limitation of the work because it considers only formal workers (those present in RAIS). But note that such an apparent limitation should now be relativized by the fact that an important part of informal workers tends to have negligible daily commuting distances since they work near their residences. In this sense, most of one of the investigated phenomena (the relevance of commuting distance) itself would impose the type of worker used in the research.

It is also important to note that, given the postulated mechanisms for the operation of the two urban characteristics of interest, at least initially, it is crucial that the individuals considered in the estimates perform occupations unaffected by shutdowns and lockdowns. In fact, as Negri et al. (2021) points out, some activities such as technical professionals, administrative and supervisory services, and education professionals, began to be carried out largely through remote work (in a home office regime). In this sense, based on information present in the Brazilian Classification of Occupations (CBO), used by RAIS, it was possible to identify essential occupations in which individuals continued to work daily during the pandemic. These are specifically: health professionals, cashier and other service workers, and police, firefighters, and security personnel. The initial sample considered in the research, therefore, relates only to workers in these occupational groups who continued their activities during the pandemic.

Table 1 below presents descriptive statistics of the variables used in the research considering the different levels of aggregation used (individuals, families, neighborhoods, and the labor market). It is important to note that a significant portion of workers did not declare their race/ethnicity. Additionally, studies such as Almagro and Orane-Hutchinson (2020) have shown that a significant portion of black and low-income workers continued to work in essential sectors of the economy in the United States, increasing their chances of contracting the virus during much of the pandemic.

Table 1 - Descriptive statistics by workers

Variables	Description	Mean	Standard deviation	Minimum	Maximum
COVID	Testing for COVID-19	0.31	0.46	0	1
Distance	Distance from the individual to the job	5.12	2.96	0	21.77
FAR	Individual's FAR	1.25	1.34	0.13	5.95
Water	Households with access the general water network	280.85	95.70	0	848
Bathroom and sewage system	Households with bathroom and sanitary sewage via general network	5.59	1.91	0	16.9
Density	Demographic density	156.95	108.38	0.03	1.817.60
Comorbidities	Individual conditions	0.08	0.27	0	1
Age	Age	40.01	11.10	15	92
Man	Gender	0.42	0.49	0	1
White	Race/color	0.20	0.40	0	1
Income	Individual income (Minimum Wage)	3.35	4.13	0	96.25
Elementary education	Completed elementary school	0.04	0.20	0	1
Completed high education	Completed high school	0.46	0.50	0	1
Completed higher education	Completed higher school	0.47	0.50	0	1
Firm size	Number of employees per establishment	7.54	2.69	1	10
Police officers, firefighters, and security personnel	Occupation	0.04	0.20	0	1
Healthcare professionals	Occupation	0.16	0.36	0	1
Cashiers and other customer service roles	Occupation	0.06	0.24	0	1
Technical-level professionals	Occupation	0.15	0.36	0	1
Administrative supervisors	Occupation	0.20	0.40	0	1
Education	Occupation	0.07	0.26	0	1

professionals					
Wholesale and retail essential trade	Economic activities	0.10	0.30	0	1
Information and communication services	Economic activities	0.03	0.18	0	1
Manufacture of essential products	Economic activities	0.01	0.11	0	1
Human health activities	Economic activities	0.15	0.35	0	1
Public administration	Economic activities	0.35	0.48	0	1
Goods transportation, postal, and transport support activities	Economic activities	0.02	0.15	0	1
Leisure activities	Economic activities	0.01	0.08	0	1
Offices	Economic activities	0.02	0.15	0	1
Food and accommodation	Economic activities	0.02	0.15	0	1

Source: authors' own elaboration.

On average, the age is 40 years, with a standard deviation of 11 years. The FAR indicates that individuals reside in homes with a higher constructive intensity than 1 and have an average income of 3.34 minimum wages, or R$2,790.62. Distances vary concerning each individual's employment, but on average, they are 2.95 km from their workplace.

The characteristics of the economic sectors and companies where formal workers operate were obtained from variables indicating the company's size in terms of the number of employees and economic activities according to the National Classification of Economic Activities (CNAE 2.0). The economic activities used were based on the categories used by Negri et al. (2021) and are considered essential as they did not adhere to lockdown during the pandemic in Recife. These include essential wholesale and retail trade, information and communication services, manufacturing of essential products, activities related to human health, goods transportation, postal services, and support activities for transportation. On the other hand, activities such as public administration, leisure, offices, food, and accommodation adhered to lockdown by government determination, being considered non-essential during this period.

4 Results

This section aims to explore the results of the study in two subsections related to economic activities that did not adhere to the lockdown period and all economic activities excluding the lockdown period.

4.1 Basiline Results

The estimates of the probability of COVID-19 contagion in the city of Recife among formal workers in activities essential to the economy, that is, those that did not adhere to the lockdown period, are presented in Table 2. In all specifications, the dependent variable indicates 1 if the individual tested positive for COVID-19 and 0 otherwise, and a set of variables related to urban characteristics, neighborhood, individual characteristics, occupation, and economic activities are used as controls. There are fixed effects for the quantity of tests performed by individuals and the month of the test. Additionally, it was also controlled whether the worker already had any comorbidity, such as heart or vascular diseases, diabetes, overweight/obesity, immunosuppression, chronic kidney diseases, chronic respiratory diseases, chronic liver disease, among others.

The Wald Test of exogeneity was statistically significant in all specifications, justifying the appropriate use of the IV probit model compared to the simple probit model. The null hypothesis of non-endogeneity was rejected. Therefore, IV probit is superior to probit, indicating the significance of error terms added to the probit equation. In these cases, both variables of interest were statistically significant, and the F-test was high in all specifications, showing that these are two good and strong instruments for analysis, as can be analyzed in the Appendix. Thus, the need for instrumental variables is justified according to this test statistic to mitigate endogeneity.

Table 2 - Urban Characteristics and Probability of COVID-19 Contagion - Essential Activities in the City of Recife.

	OLS	**2SLS-IV[I]**	**Probit**	**Probit-IV**	**Probit-IV[I]**
Intercept	0.402*** (0.028)	0.093 (0.084)	-0.968*** (0.072)	-1.954*** (0.078)	-1.495*** (0.151)
Urban Characteristics					
Distance to Employment	0.001 (0.001)	0.108*** (0.021)	0.001 (0.002)	0.236*** (0.028)	0.233*** (0.028)
Floor Area Ratio	0.004* (0.001)	0.134** (0.002)	0.010* (0.004)	0.291*** (0.042)	0.282*** (0.044)
Neighborhood					
Water	0.001 (0.001)	-0.006** (0.001)	0.001 (0.001)	-0.012*** (0.002)	-0.011*** (0.002)
Bathroom and sewage system	-0.012 (0.020)	0.272** (0.036)	-0.035 (0.058)	0.573*** (0.097)	0.561*** (0.099)
Population Density	0.003 (0.002)	0.046*** (0.005)	0.009 (0.000)	0.001*** (0.000)	0.001*** (0.000)
Individual Characteristics					
Health Conditions	-0.005 (0.006)	-0.012 (0.007)	-0.014 (0.019)	-0.004 (0.017)	-0.024*** (0.017)
Age	0.003** (0.000)	0.001 (0.001)	0.007* (0.003)	0.009** (0.004)	0.002 (0.003)
Age^2	-0.000** (0.000)	-0.001 (0.000)	-0.001** (0.000)	-0.001*** (0.000)	-0.0001 (0.000)
Male	0.025*** (0.004)	0.024*** (0.004)	0.074*** (0.011)	0.046*** (0.013)	0.047*** (0.013)
Income	0.001 (0.000)	0.000 (0.001)	0.001 (0.002)	0.0006 (0.0013)	0.001 (0.001)
White	0.009** (0.005)	0.014** (0.006)	0.026 (0.013)	0.014 (0.012)	0.026** (0.012)
Elementary Education	-0.021 (0.013)	-0.028 (0.015)	-0.063 (0.038)	-0.054 (0.033)	-0.054 (0.034)
Completed High School	-0.019* (0.010)	-0.013 (0.012)	-0.057 (0.030)	-0.029 (0.027)	-0.023 (0.027)
Completed Higher Education or more	-0.052*** (0.010)	-0.045*** (0.012)	-0.156*** (0.003)	-0.082*** (0.032)	-0.087*** (0.032)
Occupation of Individuals					
Firm Size	0.002 (0.001)	0.003* (0.001)	0.004 (0.002)	0.006** (0.003)	0.006** (0.002)
Health Professionals	0.030*** (0.005)	0.023** (0.006)	0.087*** (0.016)	0.136*** (0.033)	0.044** (0.018)
Public-Facing Roles	0.009 (0.008)	0.006 (0.009)	0.027 (0.023)	0.014 (0.020)	0.012 (0.020)

Police, Firefighters, and Security Personnel	-0.017* (0.009)	-0.013 (0.010)	-0.049* (0.027)	-0.009* (0.023)	-0.026* (0.024)
Economic Activities					
Essential Wholesale and Retail Trade	0.011 (0.007)	0.018* (0.008)	0.031 (0.020)	0.039** (0.017)	0.036** (0.017)
Information and Communication Services	0.027*** (0.010)	0.021 (0.012)	0.079* (0.031)	0.039 (0.028)	0.038 (0.029)
Manufacturing of Essential Products	0.065*** (0.016)	0.065** (0.018)	0.189*** (0.046)	0.097** (0.043)	0.1240*** (0.045)
Human Health Activities	0.062*** (0.005)	0.068*** (0.006)	0.175*** (0.016)	0.177*** (0.031)	0.129*** (0.022)
Freight Transport, Postal, and Support Activities for Transportation	0.035** (0.012)	0.034* (0.014)	0.105** (0.035)	0.048 (0.032)	0.066** (0.034)
Controls					
Number of Tests per Person	Yes	Yes	Yes	Yes	Yes
Former Train Tracks (IV)	No	Yes	No	Yes	Yes
Apartment Density (IV)	No	Yes	No	Yes	Yes
Time	Yes	Yes	Yes	No	Yes
Wald Test of Exogeneity	-	-	-	35.82***	32.16***
F-Test	43.60***	41.73***	29.33***	112.18***	112.18***
F - First Stage	24.51	-	24.51	25.41	25.41
Durbin (Score) chi2(2)		25.3***			
Wu-Hausman F (2,66155)		12.65***			
Tests of Endogeneity	-	-	13.28***	11.31***	11.31***
Observations	**66.192**	**66.192**	**66.192**	**66.192**	**66.192**

Source: authors' own elaboration.

Notes: ([I]) Probit-IV Estimation with Robust Standard Errors. Level of statistical significance: (*) P<0,1; (**) P<0,05; (***) P< 0,01.

In the urban context, the commuting distance of the worker and the constructive density of households were statistically significant. As expected, workers living farther from work have higher exposure and a greater chance of contagion. Moreover, living in high-density construction residences, such as buildings, condominiums, and slums, increases the probability of contamination due to greater sociability, compared to low-density construction residences, such as houses. Neighborhood control variables, such as the characteristics of the census tract households where the individual lives, access to the general water supply, and whether the residence has a bathroom and access to sanitary sewage, were statistically significant and indicate that having access to water reduces the chance of contagion, while households with a bathroom, access to the general sewer system, and population density increase the probability, supporting other studies such as the case investigated by Almagro et al. (2021) and Rosenthal, Strange, and Urrego (2021).

Among individual characteristics, age, gender, and white race/ethnicity showed a higher chance of COVID-19 contagion. Additionally, there is a positive relationship between higher income for these formal workers and the chance of contagion, suggesting that the higher the income, the higher the probability of contagion, as this group undergoes more tests than other workers. On the other hand, the higher the individual's education, the lower the chance of contagion, suggesting that individuals with higher education tend to have jobs with less contact with the public. In terms of firms, the size of the company is a relevant factor, so the larger the number of employees, the higher the probability of contagion.

In terms of professional occupation, the results indicate that individuals working in essential services, such as healthcare professionals, showed a robust result in all five models, suggesting that having this occupation increases the chance of contracting the virus, which is consistent with Janiak, Machado and Turén (2021). Additionally, public-facing services, whether in markets or other establishments, showed a positive and significant relationship in the first two models, suggesting an increase in virus contagion among these formal workers.

Finally, model Probit-IV (column 5 and 6) indicates that police officers, firefighters, and security personnel have a lower chance of virus contagion in the city of Recife in 2020. This is the only case that differs from the scenario in Rio de Janeiro, as highlighted by Negri et al. (2021). On the other hand, all other economic activities clearly show that essential wholesale and retail trade, information and communication services, manufacturing of essential products, activities related to human health, and the transportation of goods, mail, and support activities for transportation were the activities that presented a positive relationship with an increased chance of contracting COVID-19.

4.2 All economic activities and excluding the lockdown period

Table 3 presents the results of estimates for the period from March to December 2020, excluding the month of May, which was the lockdown period, for all activities, whether essential or not, used in the study.

In general, the magnitude of the commuting to work coefficient and the expected sign remained the same, and the FAR results were slightly higher than those presented in the previous table, controlling for non-essential activities. It is noteworthy that FAR showed a higher coefficient, even higher than the commuting distance to work, suggesting that the transmission of COVID-19 is more likely to occur where the individual lives than on the way to work. This indicates that even with remote work, there was an increase in COVID-19 contagion through constructive intensity transmission. This reinforces the hypothesis that the higher the FAR, the higher the chance of contagion, a significant finding of the study.

Table 3 - Urban Characteristics and Probability of COVID-19 Contagion in the City of Recife - Outside the Lockdown Period

	2SLS-IV[I]	**Probit-IV**	**Probit-IV**	**Probit-IV**	**Probit-IV**[I]
Intercept	-0.618* (0.246)	-1.918*** (0.074)	-1.963*** (0.072)	-1.935*** (0.076)	-1.935*** (0.076)
Urban Characteristics					
Distance to Employment	0.138** (0.043)	0.245*** (0.024)	0.245*** (0.025)	0.243*** (0.026)	0.243*** (0.026)
Floor Area Ratio	0.172** (0.056)	0.306*** (0.039)	0.306*** (0.039)	0.303*** (0.040)	0.303*** (0.040)
Neighborhood					
Water	-0.007** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)
Bathroom and sewage system	0.346** (0.116)	0.616*** (0.090)	0.613*** (0.090)	0.609*** (0.092)	0.609*** (0.089)
Population Density	0.001** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Individual Characteristics					

Individual Health Conditions (Comorbidities)	-0.007 (0.010)	-0.0106 (0.018)	-0.013 (0.017)	-0.013 (0.018)	-0.013 (0.017)
Age	0.004** (0.002)	0.007* (0.004)	0.008* (0.004)	0.008* (0.004)	0.008* (0.004)
Age^2	-0.001** (0.000)	-0.001* (0.000)	-0.001* (0.000)	-0.000* (0.000)	-0.001* (0.000)
Male	0.022*** (0.006)	0.030* (0.013)	0.032* (0.012)	0.038** (0.014)	0.038** (0.014)
White	0.008 (0.007)	0.023 (0.012)	0.009 (0.012)	0.014 (0.012)	0.014 (0.012)
Income	-0.000 (0.001)	-0.001 (0.001)	0.001 (0.001)	-0.000 (0.001)	-0.0001 (0.001)
Completed Elementary Education	-0.037 (0.020)	-0.059 (0.034)	-0.068* (0.034)	-0.066 (0.034)	-0.066* (0.035)
Completed High School	-0.013 (0.015)	-0.011 (0.027)	-0.023 (0.027)	-0.023 (0.028)	-0.023 (0.027)
Completed Higher Education or more	-0.038** (0.016)	-0.055** (0.030)	-0.082** (0.032)	-0.069** (0.031)	-0.069** (0.031)
Occupation					
Firm Size	0.000 (0.001)	0.001 (0.003)	0.002 (0.003)	0.000 (0.002)	0.000 (0.002)
Police, Firefighters, and Security Personnel	-0.001 (0.014)	-0.016 (0.025)		-0.002 (0.025)	-0.002 (0.025)
Health Professionals	0.068*** (0.009)	0.138*** (0.036)		0.112*** (0.031)	0.112*** (0.030)
Cashiers and Others in Customer Service	0.014 (0.012)	0.034 (0.022)		0.025 (0.022)	0.025 (0.022)
Technical-level Professionals	-0.014 (0.008)	-0.012 (0.014)		-0.026* (0.016)	-0.026* (0.015)
Administrative Supervisors	-0.012 (0.008)	-0.027* (0.014)		-0.023 (0.014)	-0.023 (0.014)
Education Professionals	-0.031** (0.011)	-0.078*** (0.023)		-0.058** (0.020)	-0.058** (0.021)
Economic Activities					
Essential Wholesale and Retail Trade	0.018 (0.010)		0.042* (0.019)	0.032* (0.019)	0.032* (0.019)
Information and Communication Services	0.017 (0.016)		0.041* (0.030)	0.031 (0.030)	0.031 (0.030)
Manufacturing of Essential Products	0.044 (0.024)		0.082 (0.047)	0.077 (0.047)	0.077 (0.046)
Human Health Activities	0.090*** (0.010)		0.191*** (0.043)	0.154*** (0.036)	0.154*** (0.035)
Public Administration	0.009 (0.010)		0.040 (0.021)	0.019 (0.018)	0.019 (0.018)
Freight Transport, Postal, and Support Activities for Transportation	0.027 (0.018)		0.052 (0.035)	0.049 (0.035)	0.049* (0.035)
Leisure Activities	0.071* (0.032)		0.133* (0.056)	0.127* (0.056)	0.127* (0.058)
Offices	-0.003 (0.018)		-0.010 (0.032)	-0.006* (0.032)	-0.006 (0.032)
Food and Accommodation	-0.020 (0.019)		-0.024 (0.033)	-0.036 (0.033)	-0.036 (0.033)
Controls					
Number of Tests per Person	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	Yes	Yes
Former Train Tracks (IV)	Yes	Yes	Yes	Yes	Yes
Apartment Density (IV)	Yes	Yes	Yes	Yes	Yes
Wald Test of Exogeneity	-	42.65	42.61 ***	39.92***	41.24***
F-Test	43.60***	41.73***	29.33***	33.47***	112.18***
F - First stage	23.01	-	24.51	24.75	25.41
Tests of Endogeneity	-	-	13.28***	12.23***	11.31***
Observations	59,197	59,197	59,197	59,197	59,197

Source: Authors' Own Estimation.
Notes: (I) Probit-IV Estimation with Robust Standard Errors. Level of statistical significance: (*) P<0,1; (**) P<0,05; (***) P< 0,01.

When considering a broad set of controls such as neighborhood and individual characteristics, the expected signs and the magnitude of the coefficients change little. It is noteworthy that individuals with comorbidities have a lower chance of contagion, possibly due to the adoption of more rigorous protective measures. These people are more aware of the risks associated with their health and tend to follow medical recommendations, such as wearing masks and social distancing, as well as avoiding high-risk environments. This awareness and preventive behavior, motivated by the need to preserve their health and reduce complications, consider the alerts made by WHO (2020) and the evidence from Bourdin et al. (2021).

Regarding occupations, technical professionals and those in the education sector showed negative and statistically significant results, indicating a lower chance of contagion in these occupations, as these workers were less exposed to the virus (NEGRI et al., 2021). Non-essential economic activities showed a negative coefficient, as expected, and corroborating with Janiak, Machado and Turén (2021), since activities such as education, for example, shifted to remote work, reducing the exposure of teachers to contact with students. Leisure-related activities were statistically significant and positive, although restricted by the government in the last months of 2020. However, they resumed in November, which was a month of a surge in COVID-19 cases. Office-related activities were statistically significant only in model 4, where, with a negative sign, they suggest that the migration of these activities to remote work reduced the chance of virus contagion.

Public administration and food and accommodation activities were not statistically significant. Therefore, it can be concluded that the activities considered non-essential (physical presence in the workplace) had little chance of stimulating virus transmission in the city of Recife. A possible explanation for this result is that these workers had their routine altered due to the volatility in contagion, which may have limited their exposure to the virus and reduced the probability of transmission. Additionally, government-implemented restriction measures, such as the closure of commercial establishments and the adoption of remote work, may have contributed to the decrease in virus spread among workers in these non-essential activities.

5. Robustness checks and Heterogeneities

To enhance support for the results, robustness checks and heterogeneity checks were conducted. A robustness checks was conducted to provide additional support for the obtained results. The exercise selected the first COVID-19 test conducted by the worker, as some workers are more exposed than others due to their engagement in occupations more closely associated with the frontline of virus combat, such as nurses, doctors, among others. This information is used to determine whether the results remain consistent or undergo changes. Subsequently, the heterogeneity test conducted pertains to workers' income, where the database was divided into two income groups, resulting in workers with incomes lower and higher than the sample median.

The robustness test provides additional support for the consistency of the results. Considering this, many individuals will undergo COVID-19 testing more than once. This exercise involves using only the initial test conducted for each individual. In other words, workers who underwent more than one test throughout 2020, often due to their professions (such as healthcare professionals, supermarket attendants, among others), or even those workers who expose themselves less but have some type of pre-existing comorbidity, and therefore undergo more tests than others in their workplace. Motivated by a need for a more reliable results control, in this case, four regressions were performed with this data.

Table 4 – Probit-IV Models: First test carried out by workers

	(1)	**(2)**	**(3)**	**(4)**
Intercept	-1.885***	-1.950***	-1.933***	-1.558***
	(0.1578)	(0.1493)	(0.1551)	(0.1871)
Floor Area Ratio	0.237**	0.235**	0.234**	0.268***
	(0.0764)	(0.0764)	(0.0771)	(0.0585)
Distance to Employment	0.215***	0.213***	0.213***	0.238***
	(0.0522)	(0.0525)	(0.0528)	(0.0375)
Controls				
Worker Characteristics	Yes	Yes	Yes	Yes
Neighborhood	Yes	Yes	Yes	Yes
Firms	Yes	Yes	Yes	Yes
Occupation	Yes	No	Yes	Yes
Economic Activities	No	Yes	Yes	Yes
Number of Tests per Person	No	No	No	No
Comorbidities	Yes	Yes	Yes	Yes
Time	No	No	No	Yes
Observations	54.937	54.937	54.937	54.937
Wald Test	8.67***	8.58***	8.48***	16.51***

Source: Authors' Own Estimation.

Notes: The first regression (1) pertains to worker characteristics, neighborhood, firms, number of tests per person, comorbidities, and worker occupation (CBO). The second regression analyzes the same characteristics except for worker occupation and includes economic activities (CNAE). In the third, both occupation and economic activities are included in the regressions, and finally, the fourth estimates with robust standard errors and time fixed effects; Level of statistical significance: *P <0.1; **P <0.05; ***P <0.01.

The results remain consistent, with coefficients similar to those obtained earlier. This reinforces that even when considering data for individuals who underwent more than one test, the results do not change significantly, making them robust. In general, there was not much change in the magnitude of the coefficients, the expected sign, or the significance of the FAR and commuting distance variables, providing additional support for the study's results.

In the heterogeneity test, which directly focuses on income levels, we are investigating the extent to which the results obtained thus far can be exclusively explained by certain social groups. This situation could impede the generalization of these findings to the entire population. Due to its potential significance for the city's configuration, it is regarded as a specific differentiation for workers with respect to income groups.

As demonstrated by Oliveira and Silveira Neto (2016), the city of Recife is highly spatially segregated by income, with wealthier individuals situated in more pleasant locations (such as the beach, river, and squares), and relatively close to the Central Business District (CBD), while those with lower incomes are in less pleasant areas. Furthermore, this wealthier segment of the city also tends to reside in relatively more apartments than houses, directly influencing the measure of construction intensity used in the research (Floor Area Ratio - FAR of the lot). Given the substantial differentiations by income in daily commuting and FAR, despite the controls applied in the regressions and instrumental variables (IVs), it cannot be ruled out that our evidence reflects specific virus contamination dynamics associated with income groups.

For this exercise, more specifically, the results are analyzed from two income groups, with the median as the defining element for the observation groups. The new estimates are presented in Table 5 below.

Table 5 – Probit-IV Models: Worker Group According to Income

	Income above the median				**Income below the median**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Intercept	-1.801***	-1.903***	-1.883***	-1.372***	-1.928***	-2.023***	-1.941***	-1.569***
	(0.1093)	(0.1076)	(0.1106)	(0.1803)	(0.3153)	(0.2306)	(0.2982)	(0.3947)
Floor Area Ratio	0.286***	0.282***	0.276***	0.265***	0.237	0.254*	0.244	0.261*
	(0.0372)	(0.0380)	(0.0397)	(0.0428)	(0.1611)	(0.1460)	(0.1557)	(0.1354)
Distance to Employment	0.254***	0.250***	0.249***	0.246***	0.189*	0.203*	0.193*	0.206*
	(0.0228)	(0.0239)	(0.0247)	(0.0256)	(0.1072)	(0.0952)	(0.1033)	(0.0879)
Controls								
Worker Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Neighborhood	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Economic Activities	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Number of Tests per Person	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Comorbidities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	No	No	No	Yes	No	No	No	Yes
Observations	33.181	33.181	33.181	33.181	33.011	33.011	33.011	33.011

Source: Authors' Own Estimation.
Notes: Levels of statistical significance: *P <0.1; **P <0.05; ***P <0.01.

Workers with higher income have a higher chance of COVID-19 contagion both by commuting distance and FAR. Therefore, constructive intensity and commuting distance matter. The distance and FAR coefficients varied little in relation to the main results of the study. When considering workers with lower income than the neighborhood, FAR is only statistically significant in regressions 6 and 8, i.e., when controlled for economic activities and in the overall regression (CBO and CNAE) with the time fixed effect. It is reasonable to assume that contagion may be associated with labor market dynamics when analyzing workers with income below the median, and thus, certain job characteristics make the individual more prone to contagion. In terms of distance, it was statistically significant and positive, demonstrating that there is greater exposure due to the distance to work leading to an increase in contagion.

6 Conclusions

The literature on urban economics has not yet provided solid evidence of the causal relationship between urban mobility and other city characteristics affecting the chance of COVID-19 contamination. In the Brazilian case, the main researches to date have considered the chances of contagion through characteristics of the labor market in cities and the effect of lockdown.

This study aims to contribute to a better understanding of the relationship between the urban environment and COVID-19 contagion by analyzing the influence of the duration of daily commuting and local household density. Using official data from the State Health Department of Pernambuco, together with information from RAIS/MTE, it was possible to identify the location of residence and work of individuals and, therefore, construct the two variables of interest. To avoid any bias related to the simultaneous decisions of workers and companies on location within the city, robust identification hypotheses are necessary, as the results are conditioned on these fundamental assumptions. The inclusion of instruments allowed controlling the potential simultaneity between the variables of interest and the response variable. The density of apartments per census tract in 2000 is directly related to the FAR of the most recent period, while the path of the imperial rails from the 19th century shaped the main current road characteristics of the city of Recife.

The research results indicate that urban characteristics impact the spread of COVID-19 in Recife. The commuting of workers and the type of residence were identified as transmission channels that increase the probability of contagion. That is, greater distance to work and higher constructive density in the residential lot are related to a higher risk of contracting the disease. During the May 2020 lockdown, there was observed effectiveness in controlling transmission among formal workers, exclusively through the investigated channels. The data also showed that individual characteristics, occupations, and essential economic activities influence the probability of contagion. White men, employed in companies with a large number of employees and with higher age and income, have a higher chance of contagion compared to other groups. On the other hand, workers with higher education levels presented a lower probability of contagion. These results indicate that some population groups are more vulnerable to the COVID-19 pandemic, and individual socioeconomic conditions play a fundamental role in the probability of death from the disease.

For future extensions of the research, it will be important to investigate other virus transmission channels and consider these factors in the design of prevention policies to be adopted. However, one limitation of the study lies in considering only formal workers and not capturing how these variables of interest affected the chance of contagion among informal workers, as they are not considered by the database used. Additionally, it is important to analyze the dynamics of the labor market as a whole in the Metropolitan Region of Recife and not just in Recife. However, this is another limitation of the study, considering that there is no FAR data for the municipalities neighboring Recife.

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Appendix

Initially, tests were conducted to assess the relevance of the instruments, categorizing them as strong or weak. In the first instance, a simple contagion regression was estimated, and then the equation incorporated the set of the following covariates. Generally, the inclusion of new variables in multiple regressions increases the degree of modeling adjustment but has little effect on the coefficient of the instrumental variable, which remains considerably robust. Thus, it is possible to employ any combination of instruments and explanatory variables for COVID-19 contagion.

The instruments used, both for FAR and commuting, exhibit a statistically significant coefficient of interest with a rejection probability at 1% for each type of regression: with and without covariates. Observing the first-stage estimates, it is noted that the estimate for the coefficient is high and with the expected sign. The F-statistic for the first stage is statistically significant and assumes a value that easily exceeds 10, the cutoff value suggested by Stock, Wright, and Yogo (2002). The first-stage F-test was used to evaluate the fundamental statistics of the two instruments used (in Model 2 of Table 2).

The Durbin and Wu-Hausman statistics indicated the rejection of the null hypothesis of exogeneity of the represented variable. Thus, the IV estimator is preferable to the OLS estimator. Both the Durbin test and the Wu-Hausman test (F) rejected the null hypothesis that the variables are exogenous, necessitating the use of instruments for distance and FAR. That is, the Durbin and Wu-Hausman tests indicate that the residuals from a regression of distance to employment and constructive intensity on the other variables are statistically significant when placed as regressors in a regression of COVID-19 contagion on all said explanatory variables. Furthermore, the results of the first stage provide confidence in the use of the proposed instruments; using the rail accessibility variable as a regressor for distance to employment yielded a positive and statistically significant influence. In fact, the set of statistics presented to assess the instrument provides strong confidence in its use.

Table 6 - 1st Stage estimation result

Variables	**First-stage regression of $Dist\_IV$:**		**First-stage regression of *FAR_IV***		**IV (2SLS) estimation**	
	Coef.	Std. err	Coef.	Std. err	Coef.	Std. err
Km_dist_IV	0.014***	0.002	-0.003***	0.001	-	-
FAR_IV	-0.529***	0.017	0.0229***	0.001	-	-
Distance to employment			-		0.128***	0.038
Floor Area Ratio			-		0.158***	0.050
Neighborhood characteristics						
Water	0.024***	0.003	0.023***	0.001	-0.006***	0.002
Bathroom and sewage system	-1.116***	0.129	-1.188***	0.057	0.310***	0.104
Demographic density	0.002***	0.000	0.002***	0.000	0.001***	0.000
Individual characteristics						
Individual conditions	0.052	0.042	0.0096	0.019	-0.002	0.009
Age	0.008	0.007	0.0041	0.003	0.005***	0.002
Age^2	-0.0001	0.0001	-0.0001	0.000	-0.001***	0.000
Man	0.024	0.025	-0.014	0.011	0.025***	0.005
White	-0.068**	0.030	0.034**	0.013	0.009	0.007
Income	-0.013***	0.003	0.012***	0.001	0.000	0.001
Elementary School complete	-0.008	0.084	0.049	0.037	-0.028	0.018
Complete high school	-0.043	0.066	-0.025	0.029	-0.011	0.014

Complete higher education	-0.155**	0.067	0.074**	0.030	-0.040***	0.015
Occupation						
Firm size	0.016***	0.006	-0.004	0.003	0.003**	0.001
Police, firefighters and security guards	0.077	0.059	-0.068***	0.026	-0.002	0.013
Healthcare professional	-0.013	0.037	0.076***	0.016	0.072***	0.009
Cashier service and others	0.018	0.055	-0.024	0.024	0.013	0.012
Technical level professional	0.064*	0.034	-0.061****	0.015	-0.012	0.007
Supervisors administrative services	0.072**	0.034	-0.018	0.015	-0.015**	0.008
Education Professionals	0.166***	0.051	-0.031	0.023	-0.051***	0.012
Economic activities						
Essential wholesale and retail trade	-0.077*	0.046	0.012	0.021	0.021**	0.010
Information and communication services	0.051	0.069	0.017	0.031	0.024	0.015
Manufacturing of essential products	-0.123	0.103	0.115**	0.046	0.055**	0.022
Human health activities	-0.039	0.043	0.010	0.019	0.109	0.009
Public administration	0.037	0.038	0.015	0.017	0.013	0.008
Transport of goods, mail and transport support activities	0.000	0.080	0.016	0.035	0.029*	0.017
Leisure activities	-0.068	0.140	-0.094	0.062	0.063**	0.031
Offices	0.008	0.081	-0.011	0.036	0.011	0.017
Activities related to education	-0.206**	0.053	0.043	0.024	0.025**	0.013
Food and accommodation	0.140	0.083	-0.013	0.037	-0.023	0.018
Constante	4.412***	0.164	0.883***	0.073	-0.581***	0.219
Estatística F	512.24***	-	1481.69***	-	995.78***	-
Sanderson-Windmeijer (Chi-sq)	24.24***	-	24.62***	-	19,96***	-
Sanderson-Windmeijer (F)	24,23***	-	24.61***	-	22.90***	-
Durbin (score, Chi)	-	-	-	-	25.307***	-
Wu-Hausman (F)	-	-	-	-	12.651***	-
AR Wald test (F)	-	-	-	-	11.50***	-
AR Wald test (Chi, sq)	-	-	-	-	23.01***	-
Stock-Wright LM S statistic	-	-	-	-	23.00***	-
Observation	**66.192**	**-**	**66.192**	**-**	**66.192**	**-**

Source: authors' own estimation.

Notes: Level of statistical significance: (*) *P*<0,1; (**) *P*<0,05; (***) *P*< 0,01.