Pedro Gesteira de Souza

Driving toward freedom and precarity. Assessing the impact of ride sharing apps on labor market outcomes in Brazil

RIO DE JANEIRO

2024

Pedro Gesteira de Souza

Driving toward freedom and precarity. Assessing the impact of ride sharing apps on labor market outcomes in Brazil

Dissertação de Mestrado a ser submetida à banca de Corpo Docente selecionada pelo Programa de Pós-Graduação em Economia, Instituto de Economia da Universidade Federal do Rio de Janeiro. Área de Concentração: Desenvolvimento Econômico e Social.

Orientadora: Profª. Drª. Valeria Lúcia Pero

RIO DE JANEIRO

2024

FICHA CATALOGRÁFICA

S729d Souza, Pedro Gesteira de.

Driving toward freedom and precarity. Assessing the impact of ride sharing apps on labor market outcomes in Brazil / Pedro Gesteira de Souza. – 2024.

77 f.

Orientadora: Valeria Lúcia Pero.

Dissertação (mestrado) – Universidade Federal do Rio de Janeiro, Instituto de Economia, Programa de Pós-Graduação em Economia da Indústria e da Tecnologia, 2024.

Bibliografia: f. 74 – 77.

1. Mercado de trabalho. 2. Trabalho informal. 3. Plataformas digitais. I. Pero, Valéria Lúcia, orient. II. Universidade Federal do Rio de Janeiro. Instituto de Economia. III. Título.

CDD 331.1

Ficha catalográfica elaborada pela bibliotecária: Luiza Hiromi Arao CRB/7 – 6787

Biblioteca Eugênio Gudin/CCJE/UFRJ

—

Pedro Gesteira de Souza

Driving toward freedom and precarity. Assessing the impact of ride sharing apps on labor market outcomes in Brazil

Dissertação de Mestrado a ser submetida à banca de Corpo Docente selecionada pelo Programa de Pós-Graduação em Economia, Instituto de Economia da Universidade Federal do Rio de Janeiro. Área de Concentração: Desenvolvimento Econômico e Social.

Orientadora: Prof$^{\underline{a}}$. Dr$^{\underline{a}}$. Valeria Lúcia Pero

Rio de Janeiro, 23 de julho de 2024:

Prof.ª Dr.ª Valéria Lúcia Pero
Orientadora

Prof.ª Dr.ª Ana Carolina da Cruz Lima
Universidade Federal do Rio de Janeiro
(UFRJ)

Prof.ª Dr.ª Mireille Razafindrakoto
Institut de Recherche pour le Développement
(IRD-DIAL)

Prof. Dr. François Roubaud
Institut de Recherche pour le Développement
(IRD-DIAL)

AGRADECIMENTOS

A meu avô Raphael e minha avó Sueli, donos da minha segunda casa e eternos responsáveis pela minha infância. Se pudesse escolher algo da vida para durar eternamente, seriam os almoços de domingo.

Aos meus pais, Ana e Roberval. Sou quem eu sou hoje por causa de vocês, são minhas referências primordiais. Agradeço por tudo, é a única palavra capaz de englobar cada aspecto, momento e detalhe.

Ao meu irmão Felipe, meu braço direito, quem tenho o prazer e o alento de compartilhar desse sobrenome. Estou aqui para a vida toda e sei que o contrário também vale. Agradeço sempre por isso.

Aos amigos de uma vida toda e vizinhos de quarto, Lucas e Sergio, cada palavra daqui foi feita ao som das portas batendo, do passo no taco, do cheiro de alguma panela no fogo. Agradeço por partilhar o dia a dia com vocês.

Aos amigos Andrea, Gabriel, Hugo, Jonathan, Matheus e Lucas, meu carinho por cada um não tem tamanho. Um pedaço de cada um definitivamente está aqui. Agradeço por cada momento de riso e de incredulidade.

Aos colegas de mestrado, especialmente Adriano, Marcus e Thiago, saber que dividiria sala com algum de vocês em alguma matéria era sempre uma felicidade. Agradeço cada conversa e troca durante esses momentos.

Aos colegas de atraso, não posso dizer que as sessões de estudo conjunto foram produtivas... Mas definitivamente me ajudaram a levar o peso desse trabalho de forma mais leve.

Á minha orientadora, Valéria, pela paciência homérica em me aturar falando do mesmo trabalho por quase dois anos. Agradeço muito pela disposição incessante e disponibilidade. Nossas conversas sempre me ajudaram muito.

Ao Instituto de Economia, por fornecer esse espaço de possibilidades; e ao IRD-Dial pela oportunidade de participar em um projeto tão interessante e desafiador.

À CAPES e ao contribuinte brasileiro, pelo investimento feito em mim. Espero retribuir com esse trabalho e cada passo dado em minha carreira

Ao motorista de aplicativo, pela lembrança constante da materialidade e limitação desse trabalho no meu dia a dia.

"(...) porque eles falaram que é um trabalho informal... Mas não é mano, você trabalha sem governo. Com seu próprio horário..."

(Motorista de aplicativo anônimo)

RESUMO

A introdução de aplicativos de transporte como Uber e 99 impactou significativamente o mercado de trabalho no Brasil, contribuindo para o crescimento da economia gig e criando novas formas de trabalho. Nessa plataforma, passageiros e motoristas são conectados através de um algoritmo, provocando disrupções nos mercados de transporte tradicionais e oferecendo oportunidades econômicas tanto para consumidores quanto para motoristas. Embora a flexibilidade e os baixos custos de entrada do trabalho plataformizado sejam apontados como fatores que aumentam os níveis de emprego, esse crescimento também levanta preocupações sobre a precarização do trabalho. Entre 2015 e 2018, à medida que a Uber e a 99 se expandiram nas cidades brasileiras, houve um aumento notável no número de motoristas autônomos, coincidindo com um aumento nos empregos informais. No entanto, esse período também viu uma queda acentuada na renda média do trabalho, potencialmente influenciada pela entrada dos aplicativos de transporte e pela recessão econômica no país. Este trabalho tem como objetivo analisar o impacto desses aplicativos no mercado de trabalho brasileiro através de uma análise em três etapas, utilizando dados da Pesquisa Nacional por Amostra de Domicílios (PNAD-C): estatísticas descritivas, análise de transições e uma avaliação de impacto causal. Em relação aos resultados, as estatísticas descritivas revelam mudanças no perfil dos motoristas autônomos, com um aumento de trabalhadores negros e com ensino médio, juntamente com uma diminuição nos ganhos médios por hora. Já a análise de transições fornece mais insights, indicando que muitos motoristas estavam empregados antes de se tornarem motoristas de aplicativo e continuaram nessa ocupação posteriormente, possivelmente sugerindo que o trabalho como motorista de aplicativo pode não ser tão temporário quanto frequentemente se percebe. Além disso, houve um pequeno aumento no número de indivíduos desempregados que se tornaram motoristas de aplicativo após a entrada das empresas, indicando seu papel como uma forma de renda temporária. Na avaliação causal, embora as estimativas não forneçam evidências definitivas de impacto causal, surgem insights valiosos. O número de indivíduos empregados mostra um claro aumento; em relação à renda, houve um aumento inicial após a entrada dos aplicativos, seguido por um declínio progressivo ao longo do tempo. A análise também indica uma redução nas horas trabalhadas após a entrada dos aplicativos, com os primeiros adotantes experimentando efeitos positivos e os adotantes posteriores enfrentando impactos negativos. Em relação a renda-hora, não foi identificado qualquer impacto.

Palavras-chave: Economia de plataforma, Transição, Diferença-em-diferenças, Mercado de Trabalho.

ABSTRACT

The advent of ride-sharing apps such as Uber and 99 has significantly impacted the labor market in Brazil, contributing to the growth of the gig economy and creating new forms of work. These companies connect passengers to drivers through technological platforms, disrupting traditional transportation markets and offering economic opportunities for both consumers and drivers. While the flexibility and low entry costs of gig work are argued to increase employment levels, this growth has also raised concerns about the precarization of work. Between 2015 and 2018, as Uber and 99 expanded in Brazilian cities, there was a notable increase in self-employed drivers, coinciding with a rise in informal jobs. However, this period also saw a sharp decline in average labor income, potentially influenced by the entry of ride-sharing apps and the country's economic recession. This paper aims to analyze the impact of these apps on the Brazilian labor market through a three-step analysis using data from the Brazilian National Household Sample Survey (PNAD-C): descriptive statistics, transition analysis, and a causal impact assessment. The first reveal shifts in the profile of self-employed drivers, with an increase in black workers and those with secondary education, alongside a decrease in average hourly earnings. The transition analysis provides further insights, showing that many drivers were previously employed before becoming app drivers and continued in this occupation afterward. This suggests that app driving may not be as temporary as often perceived. Additionally, there was a small increase in unemployed individuals transitioning to app driving after the apps' entry, indicating its role as an income cushion. In the causal assessment, while the estimations do not provide definitive evidence of causal impact, valuable insights appears. The number of employed individuals shows a clear increase; regarding income, there was an initial increase after the apps' entry, followed by a progressive decline over time. The analysis also indicates a reduction in working hours post-app entry, with early adopters experiencing positive effects and later adopters facing negative impacts.

Keywords: Platform Economy, Transitions, Difference-in-differences, Labor Market, Brazil.

LISTA DE ILUSTRAÇÕES

LISTA DE TABELAS

LISTA DE ABREVIATURAS E SIGLAS

PNAD-C	Pesquisa Nacional de Amostra por Domicílio - Contínua
IBGE	Instituto Brasileiro de Geografia e Estatística
CNAE	Classificação Nacional de Atividades Econômicas
CBO	Código Brasileiro de Ocupações
COD	Código de Ocupações Domiciliares
MTE	Ministério do Trabalho e Emprego
DiD	Difference-in-Differences

SUMÁRIO

1 INTRODUCTION

New technologies with the advent of transportation apps have arisen new forms of work. These apps have very low entry costs and flexibility to choose when, where and how much to work. It is natural to think that these characteristics promote an increase in employment levels. However, it has also been criticized for increasing precarity among its drivers, who are considered independent workers rather than employees. In the Brazilian context, the end of the last decade was marked by a resurgence of the economic recession based on informal jobs. Data shows that, for the period from 2016 to 2019, the population employed in formal jobs decreased by 0.4% while the population employed in informal jobs, for the same period, increased by 12% (BARBOSA, 2019).

This growth coincides with the emergence of gig workers. In the specific case of Uber and 99, the platforms analyzed in this study, which have UberX and 99POP, popular ride-sharing services targeted in this study, there was an initial presence in three major Brazilian cities at the end of 2015; but it it is from 2016 that they began to be present in a large number of cities across Brazil. This increase starting in 2016 potentially coincides with the economic recovery led by informal jobs.

The literature on the economic impact of ride sharing apps, such as consumer surplus and job market for drivers, is extensive (COHEN et al., 2016; HALL; KRUEGER, 2018; RANI, 2018). At the same time, several studies have used the staggered entry of Uber, one of the first and main ride sharing apps available worldwide, as a way to evaluate its impact on a variety of outcomes. Chang (2017), for example, found a negative impact on taxi driver earnings. Additionally, there is the study of Glasner (2022) who found a positive relationship between the minimum wage increase and work participation below the minimum wage , with the presence of the Uber app. Regarding urban outcomes, there is the work of Li, Hong e Zhang (2017) that found evidence of increased urban traffic congestion due to Uber's entry, and the study of Moskatel e Slusky (2019) who detected a reduction in the use of ambulances for low-risk patients with the uber entry.

Studies within that framework analyzing labor market outcomes have been scarce. To this date, we were only able to find one study that tries to investigate the impact of uber's entry in the labor market. Li, Hong e Zhang (2021) finds increased labor force participation and reduced unemployment in the cities that uber has entered.

In Brazil, the contribution is more limited. Oliveira e Machado (2021) evaluate the impact of Uber's entry on taxi drivers' earnings. Based on PNAD-C data for 10 capital cities in the country, they find that Uber's entry had no significant impact on taxi drivers' hourly earnings. Nazareno (2023) evaluate the impact of Uber's entry on self-employed drivers using data from PNAD-C to apply a DiD on metropolitan cities and find a reduction in income, in working hours and in the contribution to social security.

This master thesis aims to contribute to this literature on the impact of Uber's entry on labor market in Brazilian capital cities by expanding it to encompass another famous ride sharing app present in the territory, the 99 App, and performing a three-step analysis base on PNAD-C data. First, a descriptive statistics to verify if there were changes in socio-demographic characteristics of self-employed drivers comparing to other groups in periods before and after the ride-sharing apps. Second, we perform a panel data analysis to verify the dynamics of self-employed drivers transitions from and to different labor statuses; before and after the apps' entry, net of unobservable individual characteristics. Third, we propose to identify the effect of the introduction of the ride-sharing apps on the labor market in general, on self-employment and on self-employed drivers. Taking advantage of its staggered entry into Brazilian cities, we aim to use a staggered difference-in-differences econometric model, using these different entries as potential treatments.

Although there are already articles using this exogenous variation as treatment, none of them investigates the effects of apps' entry on the Brazilian labor market. This exercise is slightly reflected in the work done by Li, Hong e Zhang (2021), albeit in a different way given the intended method and the data used. Moreover, this article analyzes the Brazilian case, a country with a higher degree of informality than the United States. Therefore, different results from the discussed study can be expected.

Given the disparities in the labor market of Brazil and the United States, especially in terms of occupational composition and the characteristics of informality (MAIA; SAKAMOTO; WANG, 2019), the external validity of the articles investigating the US case is not present for the Brazilian case. Furthermore, to our knowledge, there are no similar studies focusing on Latin American countries, a category of greater similarity to Brazil (in terms of informality). Therefore, this thesis is relevant to assess not only the brazilian case, but to potentially serve as a proxy for Latin American neighbors.

As for the results, we observed changes in the profile of self-employed drivers, with an increase in black workers and workers with secondary and higher education, and a decrease in average hourly earnings. The transitions analysis are marked by an increase of self-employed driving from unemployed, discouraged and inactive statuses; and an elevated presence of individuals who stays as app driver. Moreover, income variations of transitions to self-employed are negatives before and after Uber and 99 entry. Regarding the causal assessment impact, albeit with problems regarding the parallel trends, the results of the difference-in-differences event-study outcomes to apps' entry find a late increase in the total of the occupied, and an initial increase in income followed by a progressive decline over time. The study also found a reduction in working hours after apps' entry, with those who adopted Uber or 99 earlier experiencing a positive effect and those who adopted it later seeing a negative effect.

The thesis is organized as follows: in section 2, we describe in detail the institutional background and entry of Uber and 99 in Brazilian cities. Sections 3 and 4 presents both the literature review and initial descriptive statistics. In sections 5 and 6, we present the data used and the empirical strategy chosen. The results are presented in section 7, a brief discussion is made about the research limitations and possible advancements in section 8, and finally, the conclusions are made in section 9.

2 INSTITUTIONAL BACKGROUND AND BRAZILIAN CONTEXT

Launched in 2010, the Uber app was a pioneer in the concept that later became known as e-hailing; the act of requesting a taxi through the internet, dispensing with the use of traditional methods such as phone calls or searching for taxis on the street. Since both demanders (users looking for a car) and suppliers (Uber partner drivers) are in the same app ecosystem, it is capable of reducing transaction costs on both sides, taking into account the proximity of the demander to the potential suppliers and the distance of the demanded ride to calculate both the price of the ride itself and the expected duration for the demander-supplier matching. In addition, through the app, the supplier driver is able to take the demander to their desired destination even without prior experience with the city routes; this makes the barrier to entry for a driver to become an Uber driver much lower than for traditional services, such as taxis.

Specifically, comparing with taxis, the requirements for a driver to become a ride-sharing app driver in Brazil is less stringent, as can be seen in the table 1 below.

Tabela 1 – Differences between the legal requirements for taxi and ride-sharing app driver profession

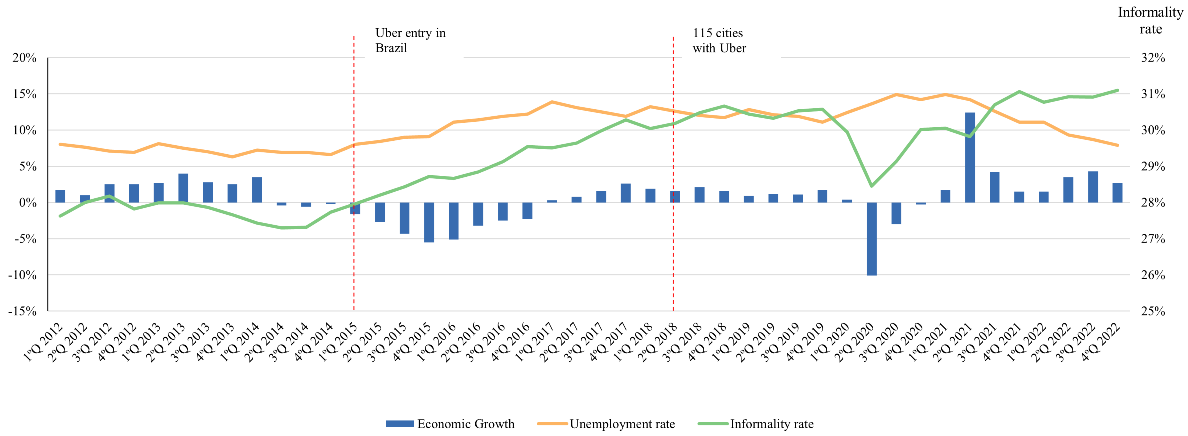
Taxi	Uber	99
• Must be at least 18 years old • Must hold a permanent B category driver's license with the notation "Exercises Remunerated Activity" • Must have a criminal record clearance certificate • Must have completed courses in human relations, defensive driving, first aid, basic vehicle mechanics and electricity, offered by a recognized entity by the respective regulatory body • Must own (or rent) a permit • Must contribute to the Brazilian National Social Security Institute (INSS)	• Must be at least 18 years old • Must hold a permanent B category driver's license with the notation "Exercises Remunerated Activity" • Vehicles with a maximum of 10 years of manufacture (or according to city regulations) • Vehicles with 5 seats, 4 doors, and air conditioning	• Must be at least 18 years old • Must hold a permanent B category driver's license with the notation "Exercises Remunerated Activity" • Regarding vehicle manufacturing age, it follows the city regulation, ranging from allowing vehicles at most 8 years old to those with a fabrication year starting in 2007. • Vehicles with 4 doors, and air conditioning

Source: Authors own elaboration.

The low barrier to entry makes it attractive for workers who have a vehicle. On the supply side, the technological innovation of the app provides space for this new job opportunity. It is noted that the low legal requirements are directly associated with the informality of the app driver. Although the taxi driver is a self-employed professional, he contributes to his retirement through the National Insurence System (INSS); while the app driver does not have this requirement.

Regarding Uber history in Brazil, the company operations began in 2014. That year was marked by the beginning of an economic and political crisis in Brazil. As can be seen in figure 1, economic growth rates were negative from mid-2014 to the end of 2016. We also see the lagging performance of the labor market, with unemployment and informality rates increasing from 2015 onwards. However, the recovery of the economy in 2017 was accompanied by a continuation of the upward trend in informality. This trend was interrupted during the pandemic crisis, but began to grow again in the following years.

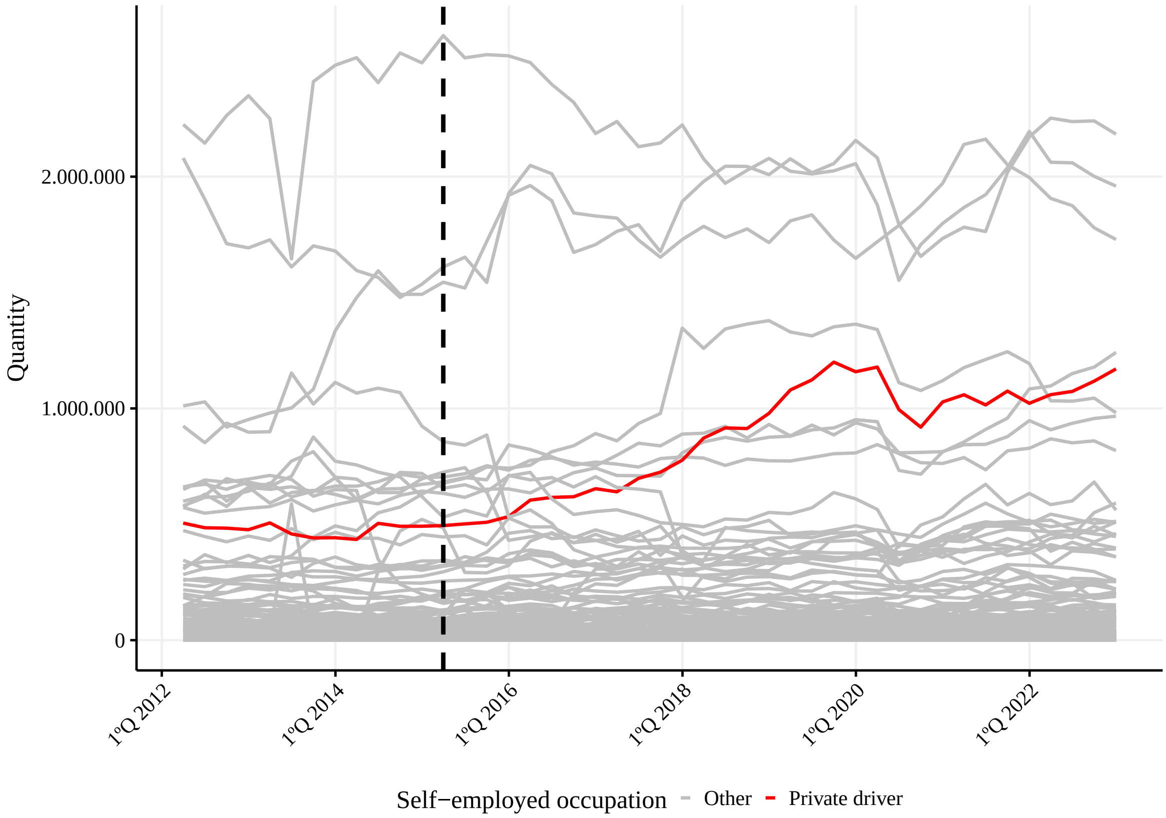
Figura 1 – Economic activity and labor market indicators in Brazil.



Source: Authors own elaboration.

The growth trend of the informality rate was pushed mainly by the increase of self-employment (PERO; MACHADO; FONTES, 2022). Figure 2 shows the evolution of the number of self-employed workers by occupation. We highlight in red the occupation of drivers and we can see a huge growth after 2015, entry milestone for UberX in many cities (99 entry happens latter, at 2016).

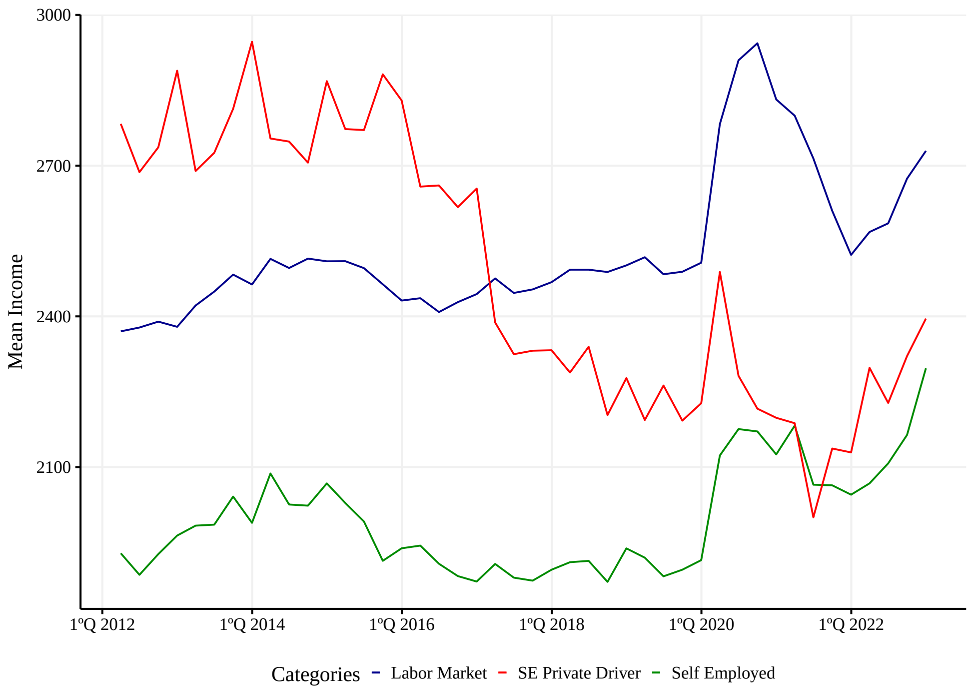
Figura 2 – Evolution of the number of self-employed by occupation.



Source: Authors own elaboration.

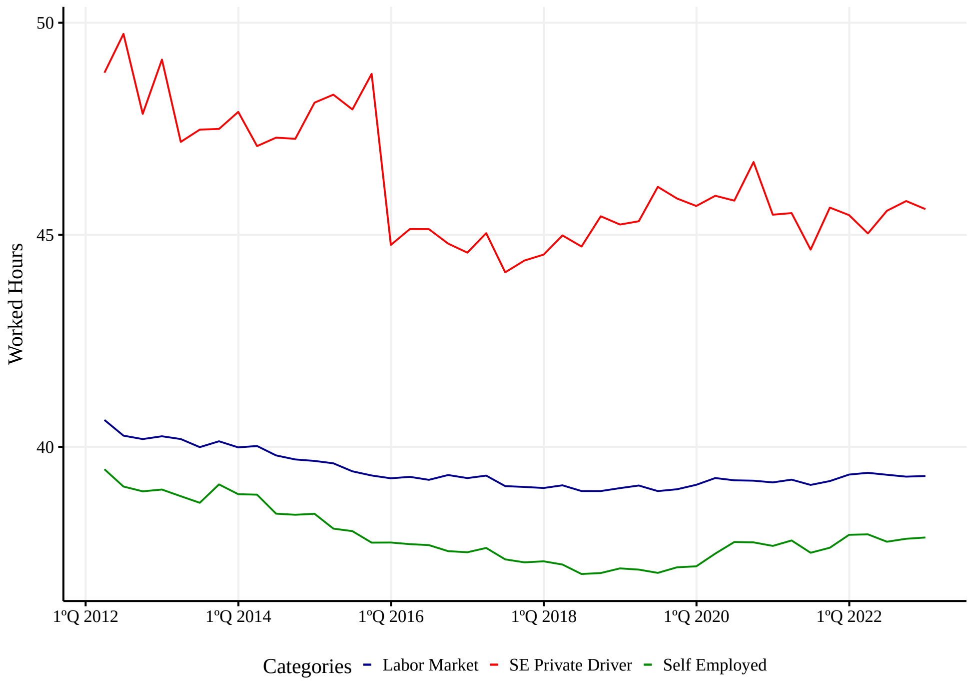
The upward trend in self-employed drivers has been accompanied by a sharp drop in average monthly earnings after 2015 (figure 3 below). This trend may be a result of the entry of Uber and 99. However, this assertion cannot be made as the country was in the middle of an economic recession, starting from 2014. Therefore, this change may be due to the growing and high unemployment rate during the period. In fact, we observe also a decrease in the average income of self-employed and all workers in the labor market. However, in the economic recovery there was a recovery in average earnings in the labor market, but not for self-employed drivers. From then on, self-employed drivers have an average income lower than the labor market average, but still higher than the average for self-employed workers.

Figura 3 – Evolution of the average monthly labor income.



Source: Authors own elaboration.

Figura 4 – Evolution of the average weekly worked hours.



Source: Authors own elaboration.

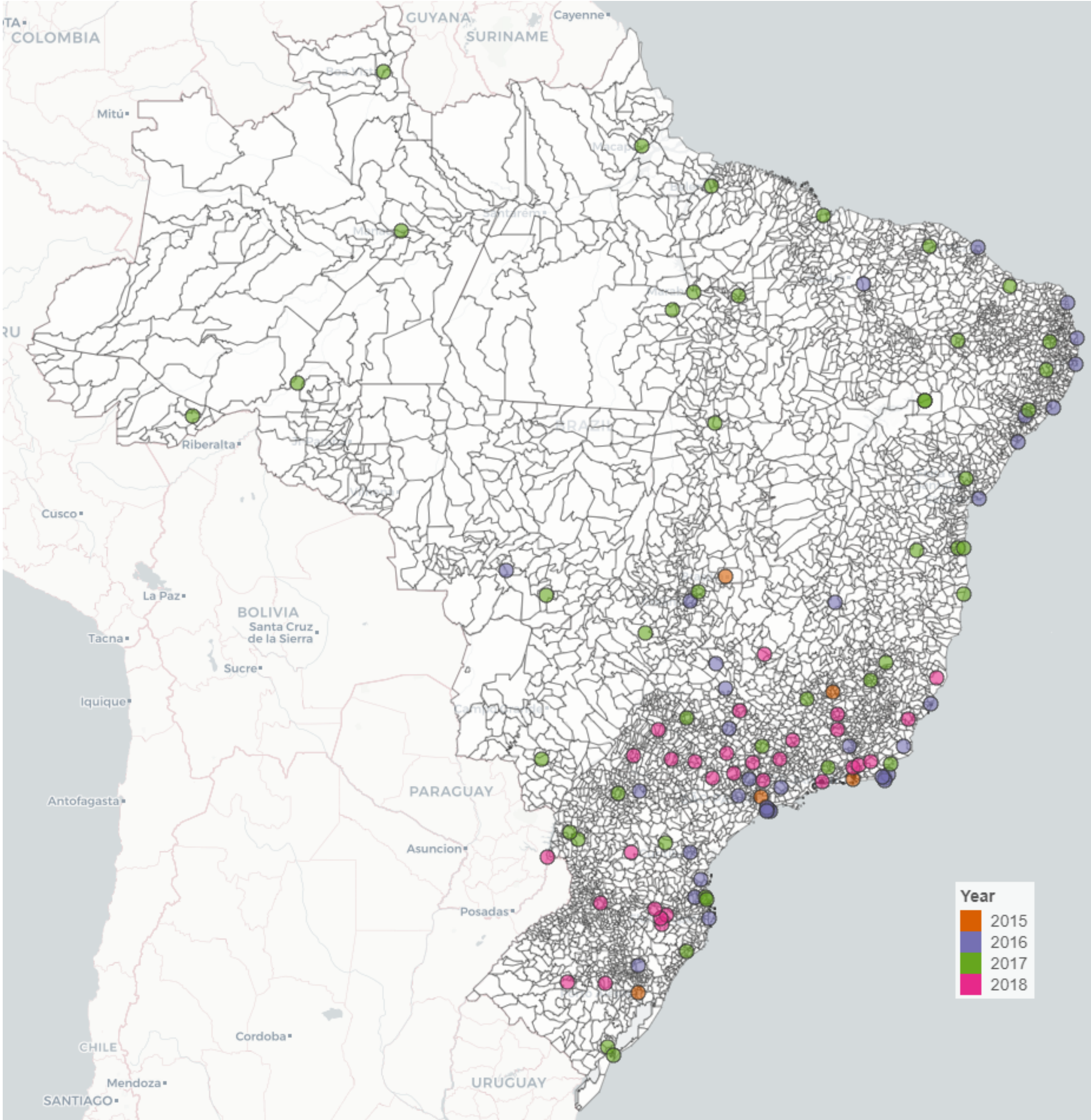
In this context, it seems that there was an adjustment in the worked hours. As we can see in figure 4, the average weekly worked hours decreases for all groups along the period. However, we observe a sharp drop in mean worked hours for self-employed drivers with the app entry and then a certain stability. It's worth noting that despite the drop, the average number of hours worked is still considerably higher than the average for self-employed workers.

In the matter of it's entry on Brazillian cities, Uber began operating in the city of Rio de Janeiro, by the year of 2014; 1 month later, it began operations in the city of São Paulo. The following year, in the cities of Belo Horizonte, Brasilia and Porto Alegre. Up to the city of Porto Alegre, the only mode available on the app was the "Uber Black", which aims to provide luxury services. More specifically, the driver must have a car with a Sedan or SUV body, a manufacturing age of up to 6 years, and specific colors (black, lead, silver, gray, navy blue, brown or white).

From Porto Alegre, Uber started offering the UberX service, concurrently with Uber Black. This service is less restrictive, and allows vehicles from the year 2010 in any colors. As it is the service with the greatest impact in terms of market job adherence, we will use the entry dates of UberX to verify the impact of Uber on the job market. This decision affects only 4 cities (Rio de Janeiro, São Paulo, Belo Horizonte, and Brasilia); due to being pioneers, these cities held Uber Black around 1 year before the launch of UberX.

As briefly mentioned in the introduction, the company's annual growth is considerable. In 2016, the app becomes available in 36 more cities. In 2017, 45 cities are added, and in 2018, another 34. This evolution can be verified in terms of space through figure 5 below.

Figura 5 – Map of Brazilian cities with UberX (2015-2018).



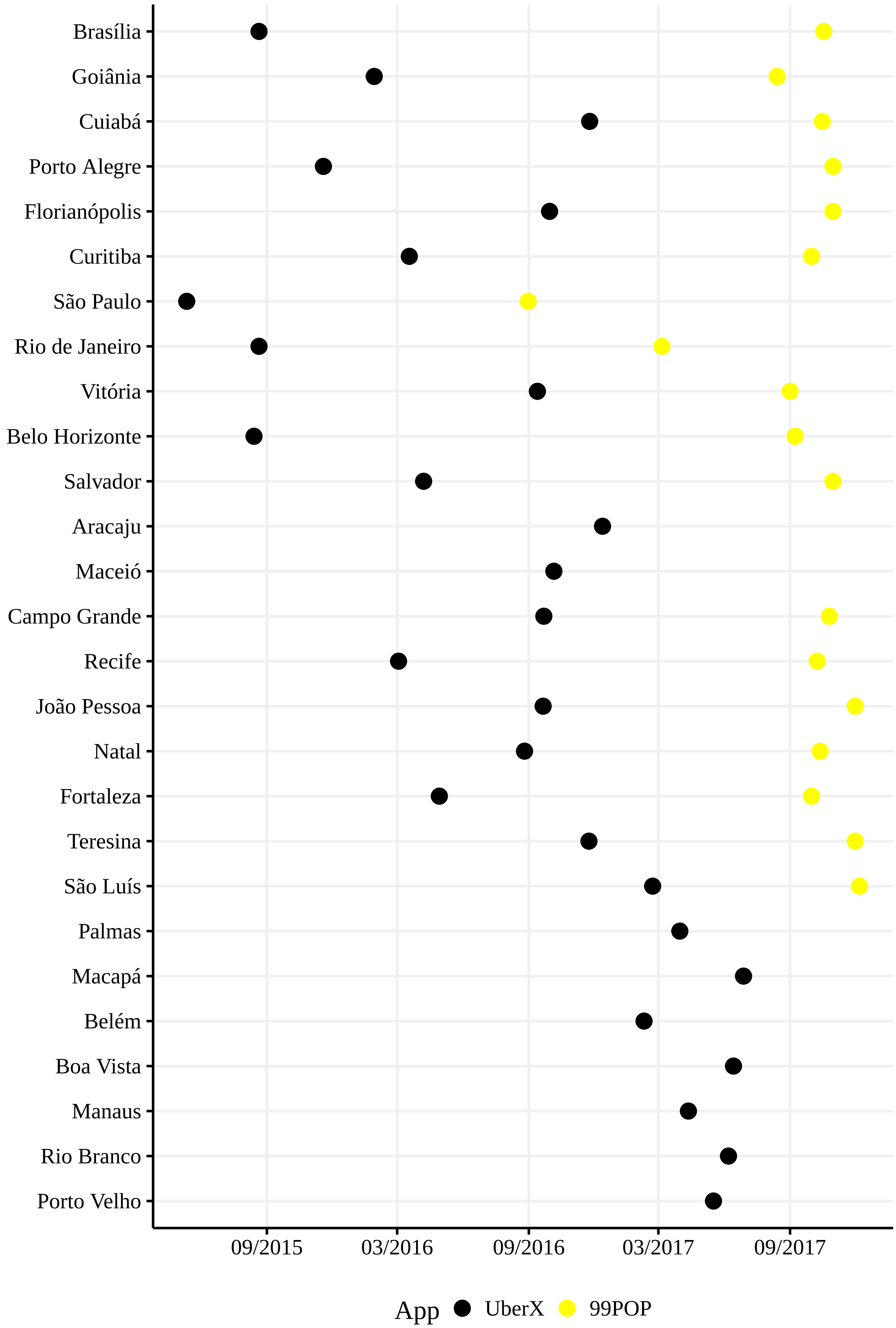
Source: Authors own elaboration.

In figure 5, it can be seen that the growth of Uber in Brazil went through several stages. Initially, there was a slow expansion in five major cities (Rio de Janeiro, São Paulo, Belo Horizonte, Brasília, and Porto Alegre). Then, starting in 2016, there was a process of expanding to the surroundings of these cities and new cities along the coast. This can be seen as an attempt to quickly establish a presence in cities with high tourist potential. In the following two years, 2017 and 2018, there was an interiorization process where Uber, already established in most capitals, expanded to less densely populated capitals and areas within states in northern Brazil. By 2018, Uber was already present in all of the brazillian capitals.

Regarding the 99 company, it was founded in 2012 and initially known as 99 Táxi.

The company started as an app connecting taxi drivers with passengers. In August 2016, the company launched the “99POP” service to compete with Uber. Through searches on news websites specific to each city, it was possible to gather entry information regarding 99POP for 18 of the 27 capitals (the other 9 capitals were not found). Analyzing its entry in relation to the entry of the UberX segment in these cities, we can observe, in figure 6 below, a strong concentration of the 99POP segment’s entry in 2017, especially in the latter half of that year; the only exceptions are São Paulo (at the end of 2016) and Rio de Janeiro (at the beginning of 2017).

Figura 6 – UberX and 99POP entry dates.



Source: Authors own elaboration.

3 LITERATURE REVIEW

Given the configuration of work for ride-sharing app drivers, there are significant theoretical synergies between this occupational setup and the informal sector. Therefore, it is interesting to address the different theoretical approaches regarding the informal sector and how these can relate to this new mode of occupation.

The literature on the informal economy is mainly divided into three approaches: the dualist, the structuralist, and the legalist approach, each with different nuances in describing the informal economy and its incentives for existence. The dualist approach treats the informal economy as a residual segment of the formal economy, positing that both form the labor market as a whole, a dual labor market in which informality results from the formal economy's inability to provide formal jobs for all individuals willing to work. Thus, particularly in crises, the informal economy becomes a safety cushion for individuals who lose their jobs in the formal economy (LEWIS, 1954; HARRIS; TODARO, 1970).

The structuralist approach evaluates the informal economy as a vital component of the capitalist mode of production. This portion of the economy, composed of small unregistered businesses or workers, becomes essential as it can provide cheap services and products to the formal economy, composed of large companies that possibly operate internationally (MOSER, 1978). Finally, the legalist approach assesses the existence of the informal sector through the transaction costs associated with the operationalization of legality. Therefore, the reason for the informal sector's existence derives from individuals' preference to operate in a way that avoids the costs associated with legality (CHEN, 2012 apud SOTO, 1989).

Evaluating the occupation of ride-sharing app driver in light of these theoretical aspects, there are elements of both the dualist and legalist approaches that can relate to the characteristics of this occupation. Given its attractiveness in terms of the flexibility it offers to the worker, this occupation is justified by the worker's ability to reconcile schedules that would not be possible in a formal job; this advantage can be interpreted as the reduction of a legality cost, which is the fulfillment of a specified working hours requirement, thus justifying the occupation's existence from the legalist approach. Regarding the dualist approach, due to the ease of entry (just having a driver's license and an available car), the occupation of ride-sharing app driver becomes a safety cushion for a segment of the population capable of working.

The literature on the economic aspects of sharing economy apps is extensive. Many studies focus on empirical investigations of microeconomic concepts, such as Cohen et al. (2016) which uses data from UberX trips to estimate consumer surplus through a discontinuity regression. The discontinuity is due to the sudden change in the fare for certain trips because of the dynamic pricing feature of the app (in areas with high demand, the price increases significantly).

Regarding the job market for ride-hailing drivers, there are several studies that use field research and/or administrative data to evaluate hourly earnings, number of hours worked, and reasons that attract workers. For example, Hall e Krueger (2018) uses a field survey conducted in the United States, with a sample of around 600 drivers, and their responses indicate that the vast majority of drivers value the flexibility offered by this type of work. Going deeper, the authors use administrative data on the activity of ride-hail drivers and find that Uber drivers take advantage of the flexibility offered by the type of work by varying the number of hours they work during the week. They also find that this group has an hourly compensation that is similar and sometimes higher compared to taxi drivers.

On a smaller scale, a similar study was conducted in Kerala, India: Rani (2018) conducts a small survey with 50 drivers and 50 customers to evaluate various socio-economic factors. As a result, it finds that the majority of drivers work for Uber as their main occupation, and the main source of complaints among this group is the price of fuel and the lack of government support for the region's infrastructure.

Additionally, there are empirical articles that use the staggered entry of Uber as a treatment in the context of using the differences-in-differences method. One such study is Chang (2017), which takes advantage of this exogenous variation and a large database of taxi trips to quantify the effect of Uber's operation on taxi driver earnings. The empirical results found by the author indicate that there is indeed a negative impact on taxi driver earnings from the entry of Uber, suggesting a substitution relationship between the service of Uber and taxi service.

Li, Hong e Zhang (2017) relies on the concept of externalities and examines whether the introduction of Uber affects urban traffic congestion. Using annual congestion data, the author indeed finds empirical evidence around this hypothesis. Glasner (2022) explores the same treatment, along with several variations of differences-in-differences, to verify changes in local labor market dynamics, with or without the presence of the app, after minimum wage increases. As a result, the author finds that increases in the minimum wage result in increases in work participation below the minimum, and this positive relationship occurs in cities with low labor market concentration and the presence of the Uber app.

The entry of the Uber app in United State cities has been evaluated in several studies, using its staged entry as a way to assess its impact on a multitude of variables. In one study (Li, Hong e Zhang (2021)), the authors assess the effect of the app's entry on unemployment in American cities, finding an increase in labor force participation and a reduction in unemployment. In another study (Moskatel e Slusky (2019)), the authors evaluate whether the app's entry reduces the use of ambulances for low-risk patients, since these patients can instead use the app for a ride. The authors find that, in fact, the entry of Uber reduces the use of ambulances for this purpose.

In the Brazilian case, Uber also had a staged entry in different cities, and some studies have taken advantage of this. Given the strong resistance of taxi drivers to Uber's entry into Brazil, the pioneering study of Esteves (2015) was carried out by the Chief Economist of the Administrative Council for Economic Defense (Cade), who obtained data on app rides, previously exclusive to taxi drivers, and checked if their revenue decreased after Uber's entry. However, the study lacks robustness, as it covers only a short period after the app's entry and has a sample of only 2 control cities and 2 treatment cities. Moreover, it does not consider the effect of Uber X in its data, the most popular category.

Finally, a last problem is that it uses a simple difference-in-differences (DiD) without guaranteeing that the parallel trends hypothesis is fulfilled. To address this deficiency, Oliveira e Machado (2021) re-evaluates the impact of Uber's entry on taxi driver earnings. Although they do not have ride data like the previous study, the authors use data from the National Household Sample Survey for 10 capitals of the country. They also control their difference-in-differences method for changes in earnings trends in other categories that may have been affected by Uber (triple differences). As a result, they verify that Uber's entry did not have a significant impact on taxi driver hourly earnings. Nazareno (2023) evaluate the impact of Uber's entry on self-employed drivers using data from PNAD-C to apply a DiD on metropolitan cities and find a reduction in income, in working hours and in the contribution to social security.

Related to descriptive analysis, Carvalho e Nogueira (2023) took advantage of the release of a special component of the PNAD-C focusing on platform workers to evaluate their demographics, income, and working hours. The study highlights how the rise of gig economy platforms, such as those used for ride-sharing and delivery services, has significantly increased the participation of self-employed workers in the transport and postal sectors. This shift has led to a noticeable decline in job security, income stability, and social security contributions for these workers. The authors argue that the expansion of platform-based work, which promotes the narrative of autonomy and flexibility, actually masks a process of labor precarization. Albeit visualizing only one point in time, the paper presents evidence showing that workers in platform jobs generally experience lower wages, longer working hours, and reduced access to social protections compared to their counterparts in more traditional employment arrangements.

As can be seen, there is no article that utilizes panel data to evaluate the dynamics of transitions related to ride-sharing app drivers. Therefore, this study is justified as it aims to shed light on these issues.

Thus, it is necessary to access the literature on approaches related to the analysis of labor market dynamics using panel data. Regarding research focused on Brazil, there are several notable contributions. Sedlacek et al. (SEDLACEK; BARROS; VARANDAS, 1990) conducted a comprehensive study on labor market segmentation and transitions for workers in São Paulo, focusing on those with and without a working card (carteira de trabalho). Using panel data collected over the period 1984-1987, they computed transition matrices to map out the movement of workers between different employment statuses, developed mobility indexes to measure the ease of these transitions, and analyzed income differentials. Their work provided early insights into the structural divides within the labor market and highlighted the differential experiences of formal and informal sector workers.

Curi and Menezes-Filho (CURI; MENEZES-FILHO, 2006) expanded on this foundation by examining sectorial segmentation and the determinants of labor market transitions across six metropolitan regions in Brazil from 1984 to 2001. They utilized a combination of surveys, transition matrices, and logistic regressions to dissect the factors influencing workers' movements between sectors. Their analysis provided a nuanced understanding of how economic, demographic, and policy variables impact labor market dynamics in different urban settings.

Aguas et al. (REIS; AGUAS, 2014) on the other hand took a different approach. By focusing on a specific subset of the labor market, discouraged workers, they developed a four-state Markov model. With it, they analyzed transition probabilities between four labor market statuses: employed, unemployed, marginally attached, and non-participating or inactive. Their study, covering the period from 2003 to 2008, revealed that the marginally attached group occupies an intermediate position between the unemployed and the inactive, sharing more characteristics with the unemployed. This finding has important implications for labor market policies aimed at re-engaging discouraged workers.

Amorim and Corseuil (AMORIM; CORSEUIL, 2016) used the panel dimension of the PNAD Contínua (PNAD-C) dataset to assess labor market adjustments during the 2014 economic crisis in Brazil. Their analysis was focused at the level of economic activities, providing detailed insights into how different sectors adjusted to the economic downturn. By examining changes in employment, earnings, and labor force participation across various industries, their work highlighted the resilience and vulnerabilities of different parts of the labor market during a period of economic stress.

Costa et al. (COSTA; RUSSO; HIRATA, 2019) studied the transitions of female domestic workers over the period 2012-2018. Their research focused on understanding the employment dynamics and economic outcomes for this often-overlooked segment of the labor force. By tracking the movements of domestic workers between employment, unemployment, and other statuses, they shed light on the precarious nature of domestic work and the factors that influence job stability and income security for these workers.

Aditionally, Júnior et al. (JúNIOR et al., 2019) utilized socio-demographic statistics to analyze the transitions of individuals between the 2017 and 2018 releases of the PNAD-C data. Their study addressed the issue of longitudinal weights, ensuring that the transitions observed in the panel data accurately reflected the broader population dynamics. Their analysis provided important methodological insights for future research using panel data to study labor market transitions.

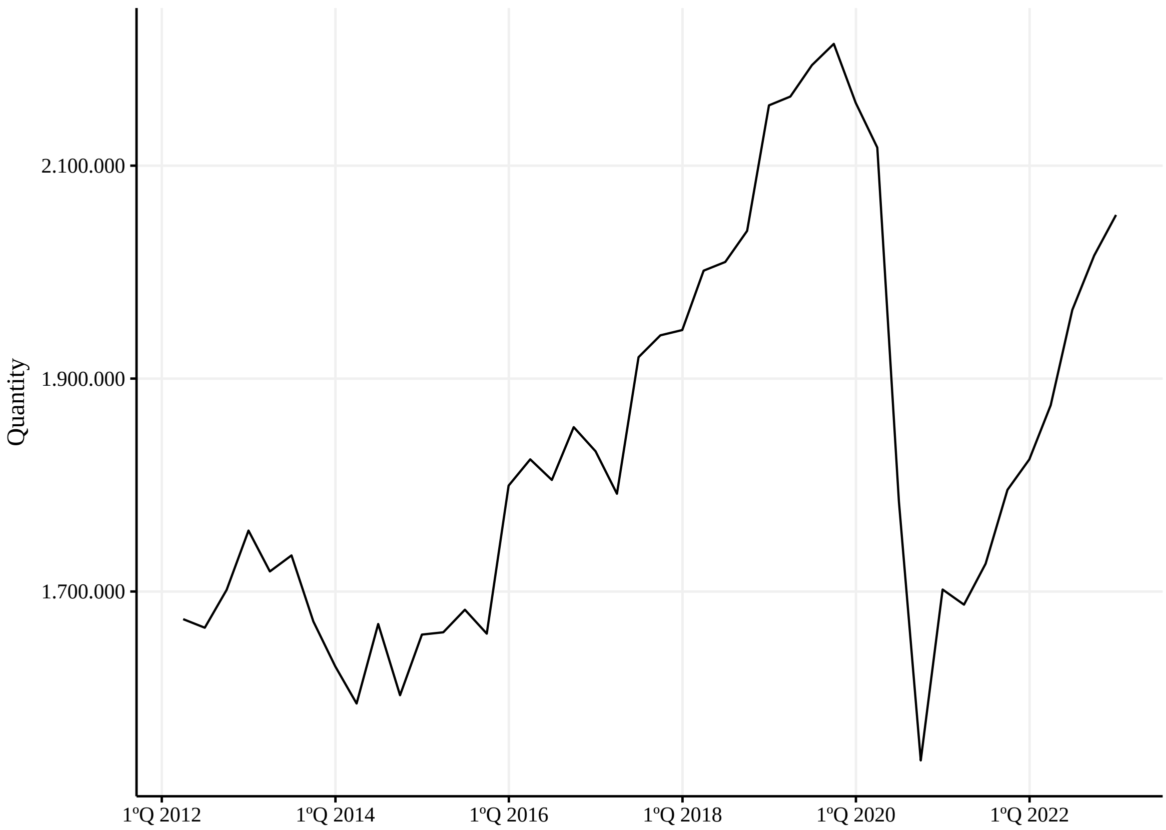
Finally, Bouvier et al. (2022) employ PNAD-C panel data to investigate the impact of the Covid-19 pandemic on the Brazilian labor market, correcting for selective attrition caused by changes in survey collection modes during the pandemic. They construct re-weighted transition matrices to distinguish five main employment statuses: formal workers, informal workers, unemployed, discouraged workers, and other inactive individuals; revealing that, despite the pandemic's significant shock, sectoral mobility rates remained constant during the crisis and even declined during the recovery, highlighting the substantial exits from informal employment to inactivity and the increasing immobility of the unemployed. This analysis underscores the critical importance of addressing the overlooked phenomenon of discouraged workers in the labor market.

These studies provide a comprehensive understanding of labor market dynamics in Brazil, using different methodological approaches to explore the interplay between formal and informal employment, economic shocks, and demographic factors. Despite this, there is a significant gap in the literature regarding the use of panel data to specifically analyze the transitions of ride-sharing app drivers. This study aims to address this gap by examining the unique labor market transitions associated with the gig economy in Brazil, altogether with a descriptive and causal impact analysis.

4 DESCRIPTIVE STATISTICS

When analyzing the transportation sector data through the PNAD-C, we can observe a significant increase in the employed population in this sector.

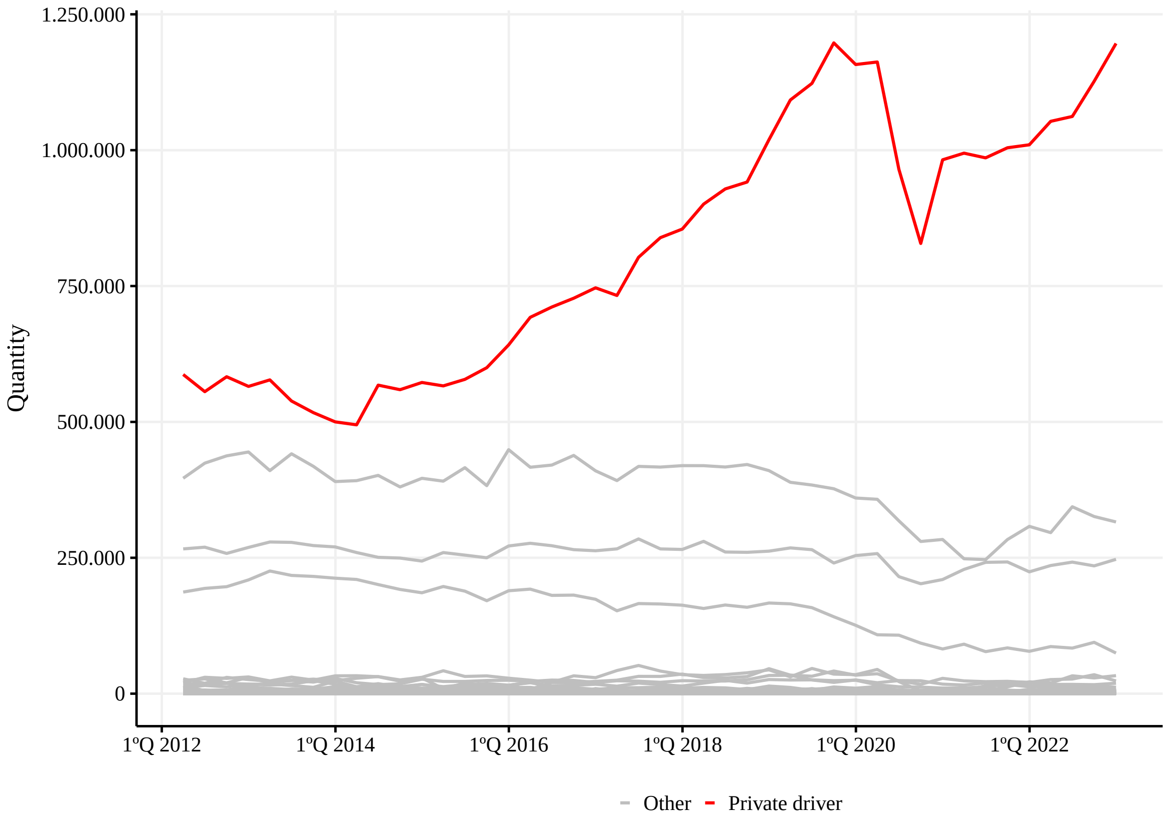
Figura 7 – Employed population in the transportation sector



Source: Authors own elaboration.

The figure above shows some stability and even a possible decrease in the employed population in the sector from 2012 to 2015. After mid-2015, the employed population dramatically increases from 1.6 million to 2.2 million by the end of 2019. Breaking down this growth into the occupations within the transportation sector, in figure 8 below, it can be seen that the growth is due to one specific occupation: drivers of cars, taxis, and vans. Although this occupation is broad and not limited to app drivers, it can be noted that the growth also begins in 2016, the year Uber and 99 presence intensified in Brazilian cities.

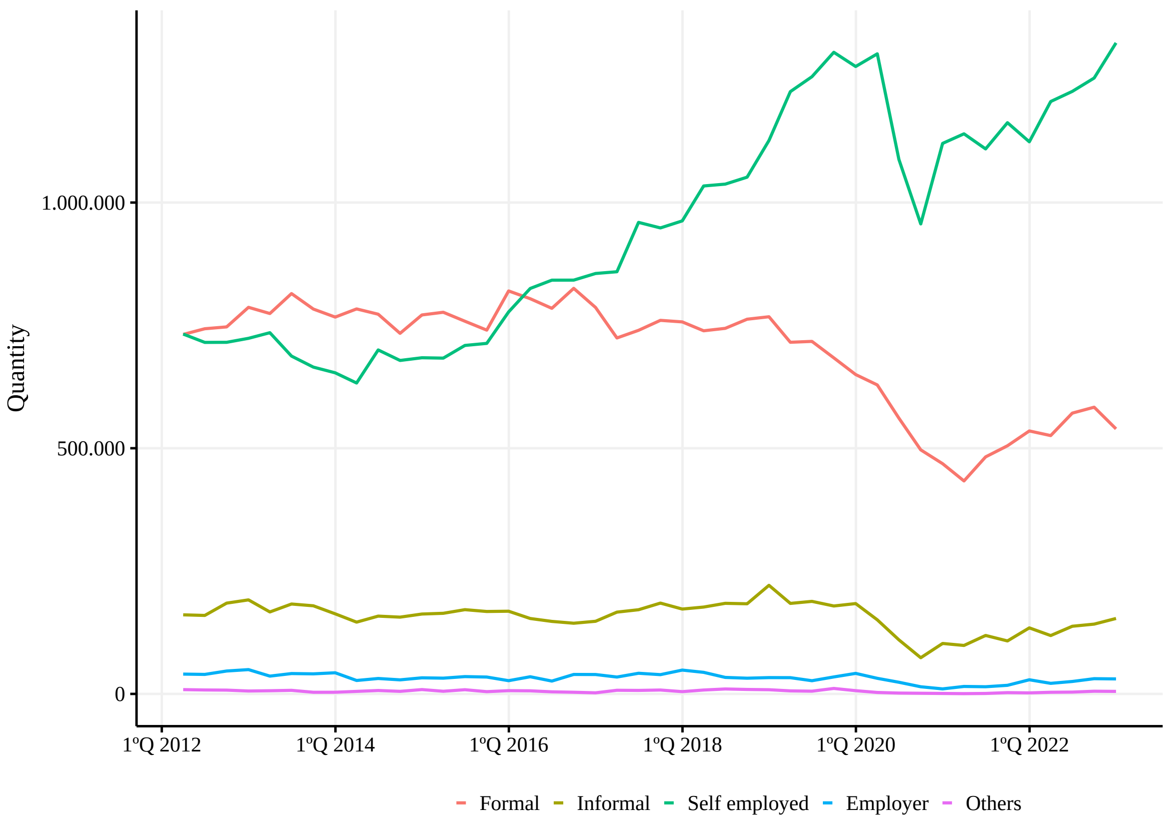
Figura 8 – Evolution of the transportation sector by occupation



Source: Authors own elaboration.

Moreover, it is observed that this evolution has a particular occupational status. From the occupational status perspective, it can be seen from figure 9 below that the self-employed category shows a divergence from its position, also starting from the years of greater presence of the apps in the cities.

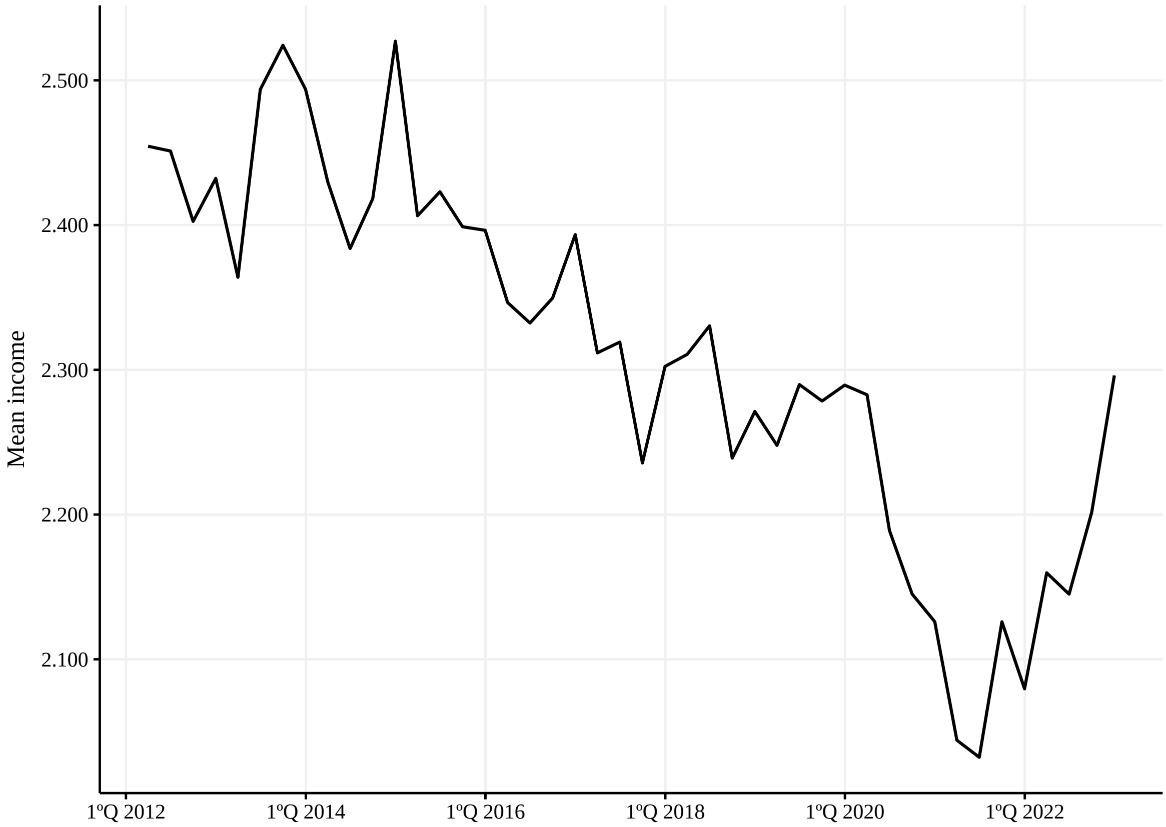
Figura 9 – Transportation Sector by Occupational Status



Source: Authors own elaboration.

Finally, analyzing the income in the transportation sector, it can be observed in figure 10 below that there is a sharp drop in the usual income of occupations in this sector. This drop may be the result of the apps' entry. However, this statement cannot be made with certainty, as the country was in the midst of an economic recession starting in 2014. Therefore, this change may be due to the growth and high unemployment rate during the period.

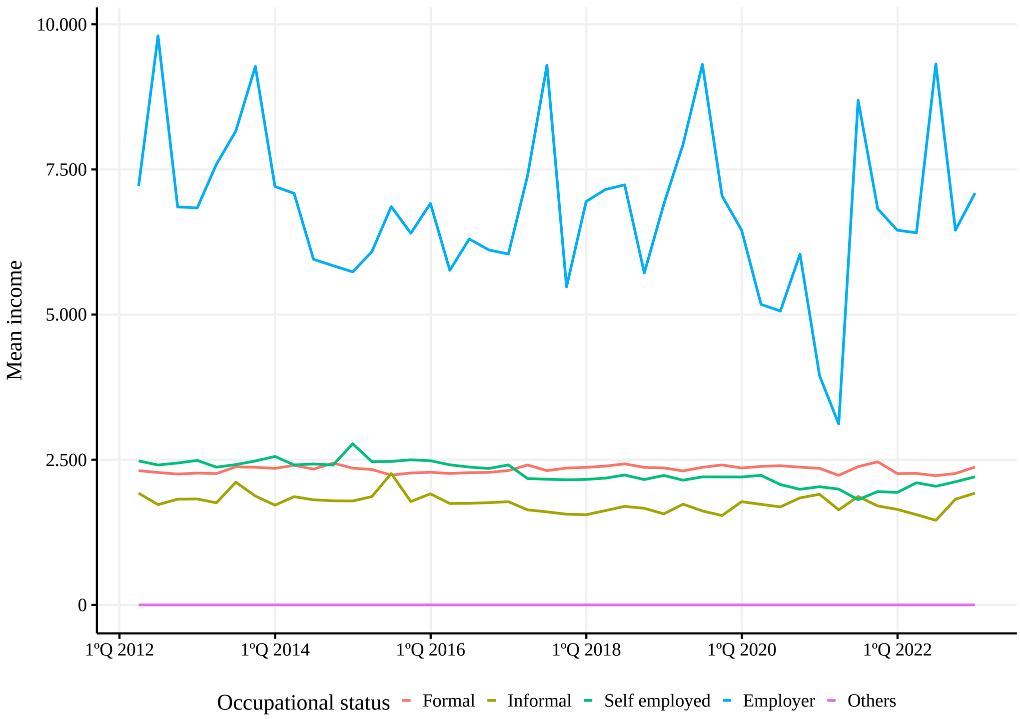
Figura 10 – Average Income in the Transportation Sector



Source: Authors own elaboration.

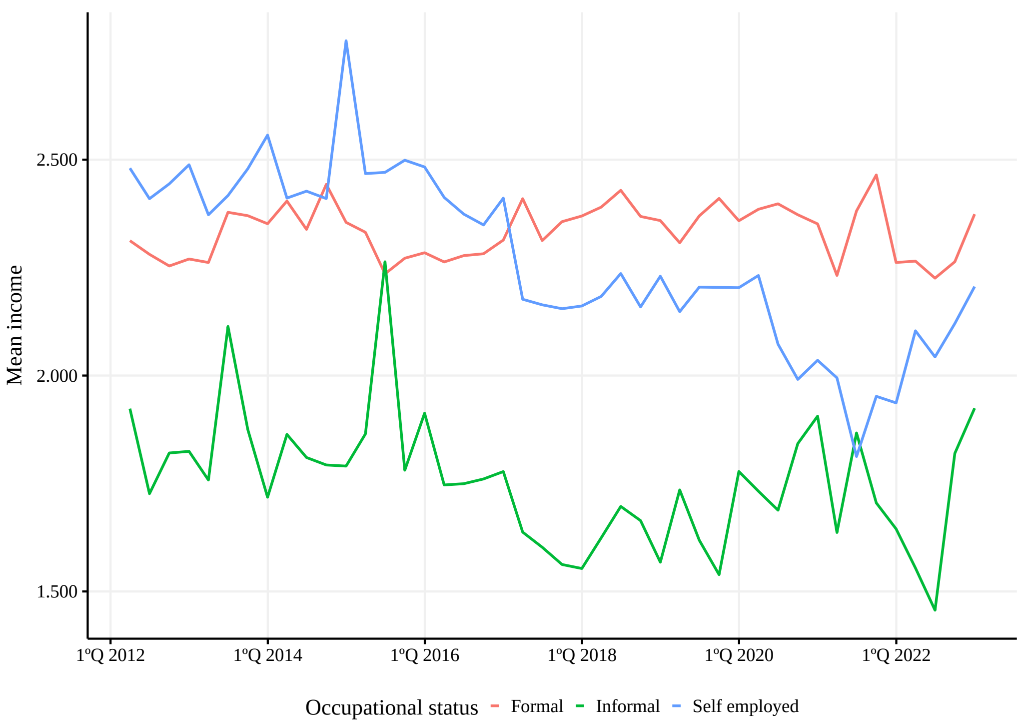
Delving into occupational status, it is possible to see in figure 11 the clear divergence between the average income of employers and those with other statuses. Because of this, figure 12 reproduces the previous figure, omitting this status to make the movements of other occupational statuses clearer. It can be observed that, while the formal and informal statuses show relative stability, the self-employed status shows a decrease in income over the quarters.

Figura 11 – Average income in the transportation sector by occupational status



Source: Authors own elaboration.

Figura 12 – Average income in the transportation sector by occupational status (without "Employer" and "Other" categories



Source: Authors own elaboration.

5 DATA

Initially, a custom-built database was constructed containing the municipalities that have Uber and the entry date of the UberX service. The database comprises the 27 capitals, of which the Uber service was entered on dates that cover the period from May 2015 to April 2018. Additionally, data from the entry date of 99POP, the similar service from 99 was also collected. Regarding this service, only data from 23 capitals were able to be collected. All the data was a result from manually finding newspaper articles regarding the entry of the service.

The database used for the proposed exercise was built from the microdata of the quarterly sample survey carried out by IBGE, the Continuous National Sample Survey of Households (PNAD-C). The PNAD-C conducts quarterly visits to households throughout Brazil in order to collect various socioeconomic information about the residents of those households, such as demographic characteristics, type of occupation, income from occupation, hours worked, etc. For each quarter, the sample contains around 550,000 observations. However, there is no information on which municipality that individual belongs to, only if they belong to one of the country's capitals. Therefore, for each instance of the survey, only observations that belonged to some capital were kept.

Each quarter, 211,000 households are surveyed following a rotating 1-2(5) scheme: a household is interviewed in one month, excluded for the next two months, and then re-interviewed, repeating this cycle five times before permanent removal. This methodology ensures that 80% of the sample overlaps from one quarter to the next, enabling the creation of a panel to study labor market transitions over up to five successive quarters.

Thus, two databases were used. First, a database containing all the individuals interviewed, stacked in the repeated cross-section format, where the quarters are stacked and each line represents an individual. The data covers individuals from 27 different cities, with a high variance in the number of observations between cities. As the survey started in 2012, and Uber's entry into the first city was carried out in mid-2015 (using the popular category UberX as reference), the chosen scope covers the 1st quarter of 2012, up to the last quarter of 2022.

Additionally, as PNAD-C operates on a rotating panel basis, a second database is built, treating the PNAD-C in the form of a incomplete panel data, enabling us to analyse job transition patterns, as elaborated below.

Despite its possibilities, working with PNAD-C as a panel presents several challenges. Since it is a survey where households are the focal point, there is no guarantee that the individual interviewed in a specific household in one quarter will be in the same household in subsequent quarters, a sample loss known as nonresponse attrition (MONTEIRO, 2019).

Additionally, there is no way to identify individuals through the survey variables, as IBGE only provides a household identifier key and not an individual identifier key for each person interviewed in the household. Therefore, it is necessary to match individuals using identifying variables (JúNIOR et al., 2019).

For this purpose, the methodology widely used in studies involving PNADC panels, developed by Ribas e Soares (2008), was employed. This methodology involves an algorithm for matching individuals that first considers the matching of households and, within each household, uses four criteria requiring equivalence in the residents' variables/characteristics as follows:

- Resident order number within the household, household position, sex, and date of birth;
- Resident order number within the household, sex, and date of birth;
- Household position, sex, and date of birth; and
- Sex and date of birth.

With the use of this matching, a sub-sample of the PNAD-C is obtained in which all individuals have information for subsequent quarters, allowing for the analysis of the sociodemographic and occupational profile of each individual in the current quarter and one year later. Additionally, to analyze shorter transitions, a sub-sample with a one-quarter difference was created, enabling the evaluation of sociodemographic and occupational changes that occurred in a single quarter.

Another typical problem with using the panel is related to sampling weights. The PNAD-C provides sampling weights to allow for population estimates of any measures and indicators derived from the survey variables (IBGE, 2014). However, these cross-sectional weights do not function as longitudinal weights (JúNIOR et al., 2019), necessitating an adjustment to this base weight to handle nonresponse attrition.

Therefore, the method used in Monteiro (2019) was adopted, where the cross-sectional weight undergoes two adjustments: the first compensates for losses relative to the original sample, and the second adjusts the sub-sample weights so that the population estimates of this sub-sample, by sex and age group, correspond to the estimates, also by sex and age group, obtained in the original PNAD-C sample, for each of the 77 estimation strata. Thus, the calculation is as follows:

$$w_j^* = w_j \times \frac{n_d}{n_d^*} \times \frac{P_{dsi}}{\hat{P}_{dsi}} \tag{5.1}$$

Where:

w_j^* = new weight in T1, calculated for each individual j in the sample;

w_j = weight for each individual j in the Continuous PNAD sample (V1028), in T1;

n_d = total number of people interviewed in the geographic area represented by estimation stratum d, in T1;

n_d^* = total number of people in the subsample, after losses, in the geographic area represented by estimation stratum d, in T1;

P_{dsi} = population estimate produced by IBGE for estimation stratum d, sex s, and age group i, on the reference date.

$\hat{P}_{dsi}$ = population estimate produced with the subsample for estimation stratum d, sex s, and age group i, on the reference date.

The sample size can be seen in the table below. In Table 2, we can evaluate the evolution of the sample in three formats: the cross-section, the theoretical panel, and the effective panel. The theoretical panel refers to the panel if there were no non-response attrition, meaning that if the individual interviewed in the first period continued and completed all five interviews. The effective panel, on the other hand, consists of only those individuals who were actually interviewed in all five interviews.

Above all, it is evident that the pandemic caused a disruption in the typical sample levels. This reduction is mainly due to the change in the interview approach. Previously conducted in person, the interviews were conducted via phone during the pandemic; this led to the loss of various households that would have been included in the sample, but for which the IBGE did not yet have phone contact data (IBGE, 2020). This issue becomes more acute in the panel, as seen by the increase in the attrition rate. The attrition rate is calculated concerning the theoretical panel, representing the percentage loss due to non-response. Generally, since we are evaluating individuals who completed all five interviews, the attrition rate shows significant values, losing on average 39% of the sample continuously. Therefore, it is necessary to apply the weight correction described earlier.

Tabela 2 – Sample size (14 years old or more)

Period	Cross-section	Theoretical panel	Effective panel	Attrition	Attrition rate
2012Q1 ⟶ 2013Q1	439.187	62.719	62.719	-	-
2012Q2 ⟶ 2013Q2	440.276	125.596	63.647	61.949	49%
2012Q3 ⟶ 2013Q3	437.688	109.531	63.515	46.016	42%
2012Q4 ⟶ 2013Q4	433.315	105.186	63.168	42.018	40%
2013Q1 ⟶ 2014Q1	441.019	111.446	65.773	45.673	41%
2013Q2 ⟶ 2014Q2	446.921	111.914	65.988	45.926	41%
2013Q3 ⟶ 2014Q3	446.470	112.918	67.819	45.099	40%
2013Q4 ⟶ 2014Q4	445.995	109.439	68.564	40.875	37%
2014Q1 ⟶ 2015Q1	450.610	111.664	69.429	42.235	38%
2014Q2 ⟶ 2015Q2	451.284	109.769	70.065	39.704	36%
2014Q3 ⟶ 2015Q3	455.778	110.375	70.763	39.612	36%
2014Q4 ⟶ 2015Q4	455.452	109.277	70.212	39.065	36%
2015Q1 ⟶ 2016Q1	455.021	108.939	69.885	39.054	36%
2015Q2 ⟶ 2016Q2	455.980	108.490	70.387	38.103	35%
2015Q3 ⟶ 2016Q3	455.977	108.129	71.583	36.546	34%
2015Q4 ⟶ 2016Q4	448.516	106.767	71.633	35.134	33%
2016Q1 ⟶ 2017Q1	452.739	108.025	72.934	35.091	32%
2016Q2 ⟶ 2017Q2	456.468	108.247	73.083	35.164	32%
2016Q3 ⟶ 2017Q3	457.654	106.803	72.863	33.940	32%
2016Q4 ⟶ 2017Q4	457.136	106.970	73.216	33.754	32%
2017Q1 ⟶ 2018Q1	459.432	107.907	73.458	34.449	32%
2017Q2 ⟶ 2018Q2	456.695	106.044	72.477	33.567	32%
2017Q3 ⟶ 2018Q3	456.138	105.571	72.031	33.540	32%
2017Q4 ⟶ 2018Q4	452.146	104.347	71.381	32.966	32%
2018Q1 ⟶ 2019Q1	451.736	105.159	71.760	33.399	32%
2018Q2 ⟶ 2019Q2	449.022	104.769	71.919	32.850	31%
2018Q3 ⟶ 2019Q3	452.269	106.867	73.007	33.860	32%
2018Q4 ⟶ 2019Q4	448.068	103.364	70.358	33.006	32%
2019Q1 ⟶ 2020Q1	447.657	103.332	65.851	37.481	36%
2019Q2 ⟶ 2020Q2	446.098	103.902	56.609	47.293	46%
2019Q3 ⟶ 2020Q3	445.422	103.434	53.487	49.947	48%
2019Q4 ⟶ 2020Q4	439.850	102.593	49.696	52.897	52%
2020Q1 ⟶ 2021Q1	396.112	82.779	39.630	43.149	52%
2020Q2 ⟶ 2021Q2	302.135	43.870	23.264	20.606	47%
2020Q3 ⟶ 2021Q3	301.724	73.774	32.032	41.742	57%
2020Q4 ⟶ 2021Q4	276.228	61.674	28.435	33.239	54%
2021Q1 ⟶ 2022Q1	263.753	70.923	30.298	40.625	57%
2021Q2 ⟶ 2022Q2	293.867	104.181	38.561	65.620	63%
2021Q3 ⟶ 2022Q3	358.211	133.324	51.274	82.050	62%
2021Q4 ⟶ 2022Q4	379.443	116.222	56.876	59.346	51%

Source: Authors own elaboration.

Futhermore, the survey includes economic activity identifiers, provided by the Classificação Nacional de Atividades Econômicas 2.0 - Domiciliar[1] (CNAE-Dom. 2.0). The CNAE Household is a classification derived from CNAE 2.0, for use in household surveys and the demographic census (Comissão Nacional de Classificação (Brazil); Instituto Brasileiro de Geografia e Estatística, 2007). And also occupation identifiers, provided by the Classificação de Ocupações para Pesquisas Domiciliares[2] (COD). The COD originated from the Brazilian Classification of Household Occupations (CBO Dom.) by IBGE, which is an adaptation of the CBO provided by the Ministry of Labor and Employment (MTE).[3]

1 National Classification of Economic Activities 2.0 - Household.
2 Occupations Classification for Household Surveys.
3 Information available at <https://www.ibge.gov.br/arquivo/projetos/sipd/oitavo_forum/COD.pdf>.

Since the occupation of app driver does not have an occupational code, the following classifications were adopted to consider an individual as having the occupation of app driver:

- Economic Activity: 49030 (Road passenger transport)
- Occupation: 8322 (Private driver)
- Occupational position: Self-employed

Additionally, the self-employed position in the occupation was considered to ensure that private drivers not related to platform drivers are properly excluded. Although this occupational set (selection of economic activity, occupation code, and occupational position) includes more than just app drivers, encompassing private drivers and self-employed taxi drivers, the analysis over the years allows for comparisons between this group before and after the entry of apps.

While the portion of private drivers does not interact with app drivers, taxi drivers can be a problem. Since app drivers provide a service very similar to that of taxis, their entry affects taxi drivers' income as well. Therefore, any measures generated for this occupational set should be understood as net of the dynamics between taxi drivers and app drivers.

Access in 25/06/2024.

6 EMPIRICAL STRATEGY

The empirical strategy is based on a three-step analysis to evaluate the effects of ride-sharing apps' entry in Brazilian capitals. First, a descriptive statistics by socio-demographic groups one year before and one year after the apps' entry in the capital cities.

Secondly, we will conduct a two-way transition analysis to investigate how app drivers were positioned in the labor market one year prior and one year after. This involves evaluating the group of individuals who are identified as app drivers in interview 5 in terms of different sociodemographic aspects during their first interview, one year prior; and examine how app drivers identified in interview 1 as such are positioned one year later, in their 5th and final interview.

Third, we will estimate the causal effect of Uber and 99 entry with a staggered difference-in-differences (DD) model using the method proposed by Callaway e Sant'Anna (2021) for estimating group-time average treatment effect ($ATT(g,t)$).

Regarding the transition analysis, the panel component of the PNAD-C makes it possible to identify the job transition from different labor force status to app driver before and after the entry of the ride-sharing apps, and vice versa (the job transition from app driver to different labor force status). We select each app driver, who appears as such in it's 5^{th} and final interview in quarter q of year y and check their labor force status in the same quarter of the previous year (or the app driver who appears as such in it's 1^{st} interview and check their labor force status one year later. We then calculated for each quarter the proportion of app drivers according to their labor force status in the previous period.

We consider four labor force statuses (BOUVIER et al., 2022):

- Occupied;
- Unemployed;
- Inactive "discouraged" (potential labor force, since the person is available to work but not seeking a job);
- Other "inactive" (other inactives like students, retireds, etc. out of the labor force).

The sum of the transitions from these four situations to app driver is 100%. The aim here is to analyze whether there have been changes over time in the transitions of these labor statuses to self-employed drivers. Regarding the occupied, we open this category to assess the occupational position. The possible openings are divided as follows:

- Formal (employees with a formal labor contract, military personnel, and civil servants);
- Informal (employees and domestic workers without a formal labor contract, and unpaid family worker);
- Self employed;
- Employer.

The question to be addressed at this point is what kind of transition has changed most since ride-sharing apps' entry. Is there an increase in the proportion of the transition from unemployment to self-employed drivers after the entry? Or has this increase been more significant from the inactive status? Furthermore, questions related to transitions regarding the work status and the occupational position of the app drivers in their final interview are to be addressed as well. To which work status do the app drivers transition in their final interview? Do they move to other occupational positions, or do they remain as drivers?

Finally, we select only the transitions from job status of the occupied workers to self-employed drivers (or vice versa) to calculate the income variation. The job status are formal employees (private and public), informal employees, self-employed and employers. Is the transition from formal employee to self-employed occurred with increase in mean earnings? Is there differences between job statuses? The income variations change over time?

The advantage of this panel data analysis is to find out whether there were changes in the dynamics of the driver's occupation after apps' entry, net of unobserved individual heterogeneity. Furthermore, we complement this analysis with a multinomial logistic regression to provide additional econometric insight into the sociodemographic dimension of the transitions of app drivers to other employment statuses.

The model estimates the log-odds of each outcome relative to a baseline category. Let Y be the outcome variable with K possible transitions. For the i-th observation, let $\mathbf{X}_i$ be the vector of predictor variables. The model can be expressed as:

$$\log\left(\frac{P(Y_i = k)}{P(Y_i = K)}\right) = \beta_{0k} + \beta_{1k}X_{1i} + \beta_{2k}X_{2i} + \ldots + \beta_{pk}X_{pi} \quad \text{for } k = 1, 2, \ldots, K-1 \quad (6.1)$$

where β_{0k} is the intercept for transition k, and β_{jk} are the coefficients for the predictor variables X_{ji} for transition k. The transition K serves as the reference transition.

The probabilities for each transition can be derived from the log-odds:

$$P(Y_i = k) = \frac{e^{\beta_{0k}+\beta_{1k}X_{1i}+\beta_{2k}X_{2i}+\ldots+\beta_{pk}X_{pi}}}{1+\sum_{j=1}^{K-1} e^{\beta_{0j}+\beta_{1j}X_{1i}+\beta_{2j}X_{2i}+\ldots+\beta_{pj}X_{pi}}} \quad \text{for } k = 1, 2, \ldots, K-1 \tag{6.2}$$

$$P(Y_i = K) = \frac{1}{1+\sum_{j=1}^{K-1} e^{\beta_{0j}+\beta_{1j}X_{1i}+\beta_{2j}X_{2i}+\ldots+\beta_{pj}X_{pi}}} \tag{6.3}$$

In multinomial logistic regression, the probability of each outcome category is modeled as a function of one or more predictor variables. The model estimates the log-odds of each outcome relative to a baseline category. Interpreting the coefficients in multinomial logistic regression involves examining the the odds ratios, the exponential of the log odds ratio. A positive coefficient indicates that as the predictor increases, the odds of the outcome category relative to the reference category increase. Conversely, a negative coefficient suggests that as the predictor increases, the odds of the outcome category relative to the reference category decrease.

Lastly, in order to estimate the causal effect of apps' entry into a city, one can consider the presence of the apps as a treatment within a framework of the difference-in-differences (DiD) estimation model.

The DiD model leverages the structure of a natural experiment, common in natural sciences, to examine the existence and magnitude of a specific causal relationship. More specifically, the model compares the change over time between a treated group (exposed to a particular intervention) and a control group (not exposed to the intervention), thus enabling control for unobservable factors that remain constant over time within each group. Consequently, the identified change can be interpreted as the causal effect of the treatment.

In its simplest form, this effect is derived through a double subtraction. Initially, the difference in the outcome for the treated group before and after the treatment, as well as for the control group before and after the treatment, is calculated. This first difference eliminates biases associated with group-specific characteristics. The second difference involves subtracting one from the other to eliminate any temporal effects associated with the passage of time since the initiation of the treatment. This resulting measure represents the difference-in-differences (DiD) estimator (ANGRIST; PISCHKE, 2009).

This double differencing can be represented in a regression equation:

$$Y_{dt} = \alpha + \beta TREAT_d + \gamma POST_t + \delta_{rDD}(TREAT_d \times POST_t) + e_{dt} \tag{6.4}$$

Where:

- $TREAT_d$ consists of a dummy representing the treatment units, with the subscript d denoting each of these units.

- $POST_t$ consists of a dummy representing the post-treatment periods, with the subscript t denoting each unit of time.

- δ_{rDD} captures the causal effect of interest, associated with the interaction $TREAT_d \times POST_t$, representing the treated units in the post-treatment period.

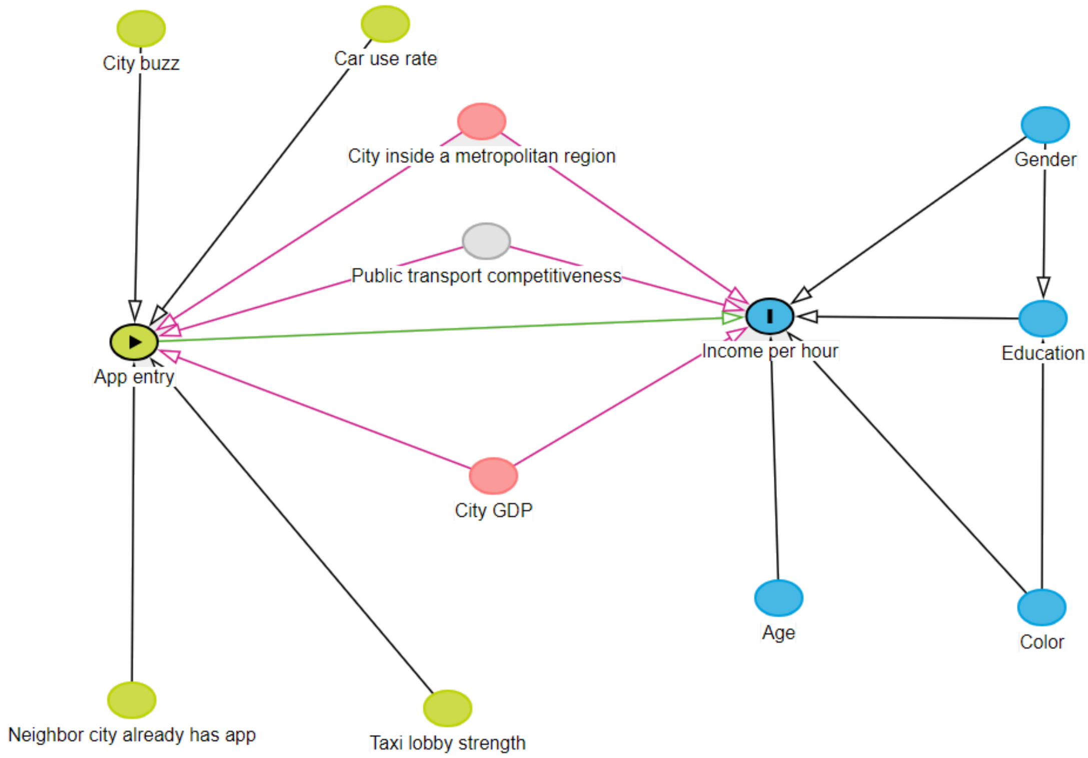
Several particularities associated with the proposed research object make the simple model of difference-in-differences not work. Firstly, since each location had the entry of Uber and 99 at different times, the treated units did not receive the treatment at the same time, it was phased. Furthermore, as the treatment effect may have a dynamic character over time, using Two Way Fixed Effects Regression would lead to a negatively biased estimator (CALLAWAY; SANT'ANNA, 2021). Therefore, the traditional estimation method is not sufficient to capture the proposed causal effect in this study. Thus, we investigate the literature of recent advances in DiD in order to accommodate the peculiarities of the research object; due to its flexibility and ease of implementation, the approach proposed by (CALLAWAY; SANT'ANNA, 2021) is chosen, with the following equation to be estimated:

$$Y = \alpha_1^{g,t} + \alpha_2^{g,t} Gg + \alpha_3^{g,t} 1\{T = t\} + \beta^{g,t}(G_g \times 1\{T = t\}) + \gamma X + \epsilon^{g,t}. \tag{6.5}$$

Where Y represents the labor market variables to be analyzed: number of occupieds in the city, labor income usually received per month, weekly worked hours and income per hour; $\alpha_2^{g,t} Gg$ and $\alpha_3^{g,t} 1\{T = t\}$ represents, respectively the group and period dummy; $\beta^{g,t}$ represents the group-time ATT, since $(G_g \times 1\{T = t\})$ represents the group-time interaction dummy that allows the calculation of the $ATT(g, t)$; finally, X represents a vector of covariates.

The chosen covariates aim to circumvent possible differences between cities that affect the parallel trends hypothesis. Since there could be several reasons to believe that these cities have different characteristics that may impact our outcome variables, we investigated the causal relations between the treatment and the outcome in search of possible confounders, variables that affect them both, and arranged it in a directed acyclical graph (DAG). It aims to provide a nuanced understanding of how the introduction of app-based transportation services reshapes the labor market dynamics for app drivers and what factors contribute to their income levels.

Figura 13 – DAG on the causal relation regarding app entry and income per hour



Source: Authors own elaboration.

The entry of app-based transportation services in a city is influenced by several factors. Firstly, "City buzz" represents the potential marketing that the city could give to the app (Uber first city to enter was Rio de Janeiro, mainly because the olympics was being held). Secondly, the "Car use rate" in the city can determine the demand and feasibility for app-based transport services. The strength of the taxi lobby can also influence app entry, as resistance from existing taxi services can affect this entry. Finally, the presence of app-based services in neighboring cities can facilitate or pressure the entry of similar services. As for the factors affecting only the hourly income of app drivers, it has an array of sociodemographic variables, such as gender, education, age, and color. Both these set of factors only influence the app entry or the hourly income, not both at the same time, so it won't be necessary to use them as covariates in the model.

At last, there's the factors that both influence the app entry and the hourly income of the app drivers. Such as the location of the city within a metropolitan region, as cities within larger metropolitan areas where the first to be available by the transport apps and may have different dynamics of rides, affecting the hourly income also. Public transport competitiveness is another crucial factor, as the strength and efficiency of public transport options can influence both the necessity and attractiveness of the ridesharing apps as well as it's rides altogheter. Additionally, economic prosperity, represented by the city's GDP, can impact both the demand for and the viability of app services. As these sets of factors both affect the treatment and the outcome variable, they are needed to be included as covariates in the model.

7 RESULTS AND DISCUSSION

In this section, we present the results of the three-step analysis to evaluate the effects of ride-sharing apps' entry on labor market in Brazilian capitals.

7.1 Descriptive Statistics of before and after ride-sharing apps

Table 3 shows the differences in the profile of employed workers one year before and one year after Uber and 99 entry, comparing the labor market in Brazilian capitals with the selective group of workers in the transportation sector, drivers and self-employed drivers (used as reference for the app drivers). First, the table shows a gender difference, with a greater presence of women in the labor market as a whole than in the transport sector. The difference is even greater when considering the group of drivers, where 93% are men and there has been no significant change since the entry of the apps.

Tabela 3 – Demographic characteristics

Characteristic		Capitals		Transport Sector		Driver		SE Driver	
		12m before UberX	12m after UberX	12m before UberX	12m after UberX	12m before UberX	12m after UberX	12m before UberX	12m after UberX
Gender	Male	47%	48%	86%	90%*	93%	93%	92%	93%
	Female	53%	52%	14%	10%*	7%	7%	8%	7%
Color	White	47%	45%*	41%	38%	49%	43%*	53%	44%**
	Black and Indigenous	53%	55%*	59%	62%	51%	57%*	47%	56%**
Education	Incomplete Middle Education	32%	30%	20%	18%	21%	16%	21%	15%*
	Complete Middle Education	15%	14%	20%	18%	20%	14%***	20%	14%**
	Complete Secondary Education	31%	31%*	54%	58%	54%	60%***	52%	60%**
	Complete Higher Education	22%	24%***	6%	7%	6%	10%***	6%	11%*
Ocupational Types	Employee	69%	66%***	54%	50%	17%	16%**	-	-
	Employer	4%	5%	3%	1%***	5%	0%**	-	-
	Self Employed	20%	23%***	43%	49%**	78%	83%***	100%	100%
	Others	6%	6%	0%	0%	0%	0%	0%	0%
SE Driver	SE Driver 1 Job	-	-	-	-	-	-	98%	97%
	SE Driver 2 Job	-	-	-	-	-	-	2%	3%
Age	Average Age	34	35	41	42	45	43*	46	43***
Income	Average Income (R$)	3.827	3.796	2.971	2.683**	3.583	3.034	3.610	3.117***
	Average Income per Hour (R$/h)	16	18	10	11	12	12**	12	13*
Social Security Contribution	Yes	73%	72%	67%	66%	53%	52%*	48%	48%*
	No	27%	28%	33%	34%	47%	48%*	52%	52%*

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ represent statistical significance levels based on a Student's t-test for means.

Source: Authors own elaboration.

Second, we can observe a higher proportion of black workers in the labor market in capitals as well as in the transport sector and for drivers. However, for self-employed drivers the proportion of white workers is higer than black before the entry. There was an increase in the participation of black workers in all the groups analyzed. It is worth noting, however, that the increase was more significant for self-employed drivers, as the proportion of blacks was higher than that of whites a year after the entry.

Analysing the educational profile, the proportion of workers with secondary education is higher in the transport sector and among drivers than in the labor market as a whole. On the other hand, the proportion of workers with higher education is lower in the transport sector. However, there has been a significant increase in the proportion of workers with completed secondary and higher education among self-employed drivers, from 58% before the entry to 71% after the entry.

The average age of employed people in Brazilian capitals was 34 before apps' entry and rose to 35 after apps' entry. The average age in the transportation sector is higher and has risen over the period from 41 to 42. In the case of drivers, the average age is even higher, but decreases after apps' entry. For self-employed drivers, it went from 46 before apps' entry to 43 after apps' entry.

The occupational types in the capitals have a higher proportion of self-employed in the transport sector and among drivers than in the capitals' labor market. In contrast, all other occupational types have a lower proportion. This higher share of the self-employed is even greater among drivers and increases in all the groups analyzed.

In terms of labor income, both median income and hourly income are higher in the capital and have remained almost constant over the period. The income of transport workers and drivers fell significantly after apps' entry. However, when evaluating hourly income, there was a slight increase.

Finally, the percentage of workers who contribute to social security in the capitals is much higher than in the transport sector and among drivers. There has been a slight decrease over time. It is worth noting that the majority of self-employed drivers do not contribute to social security (52%).

This analysis has shown that there have been significant changes in the profile of self-employed drivers in terms of color (an increase in the proportion of blacks), education level (an increase in the proportion of workers with secondary and higher education) and mean labor income, which has decreased significantly after apps' entry.

Regarding the statistical significance of these changes, we conducted an analysis through a t-test for the difference in means. Through the test, it can be seen that some of the previously described movements have some statistical support. Although the difference in gender does not present significance, it is noted that the deepening of racial inequality is significant for the samples of drivers in general and app drivers. Regarding educational changes, all prove to be significant, suggesting an increase in those employed with completed secondary or higher education, with a greater increase in the former. Given that this occupation requires both a prior qualification (driver's license) and the possession or rental of a car, and both requirements have some positive correlation with income, and consequently, with education, the larger share of those employed with completed secondary education makes sense.

On the occupational positions, the increase in self-employed workers, although it is a labor market trend, appears to be related, in the transport sector, to the emergence of this new occupation. This new occupation also seems to have changed the age composition of drivers, given that there was a reduction in the average age, which is statistically significant. Both income and social security contribution also show changes; although the latter has only seen a decrease of tenths, the former presents more substantial changes.

7.2 Changing dynamics to app drivers

To provide a more detailed overview of the increase of drivers' self-employment, we will complement it with a dynamic analysis based on the transitions from different labor force statuses (occupied, unemployed, discourage and inactive) to self-employed driver over time, the "prior", and the transitions from self-employed driver to different labor force statuses, the "after".

Both will be measured in terms of the proportion of the employed and the income difference in the transitions. The objective is to gain an understanding of the different occupational statuses of the workforce who became self-employed drivers and to understand where these self-employed drivers transitioned to afterward (if they transitioned), also in terms of occupational status.

Evaluating the "prior", table 4 below presents the annualized measure of the proportion of individuals who became app drivers in the following year by work status. It can be verified that a large part of the drivers were already in some occupation before transitioning to app driver. Nonetheless, it is possible to identify an increase in the unemployed status over the years, indicating the attractiveness of this form of work in terms of capturing the portion of the population with this work status.

Tabela 4 – Proportion of the sample by work status

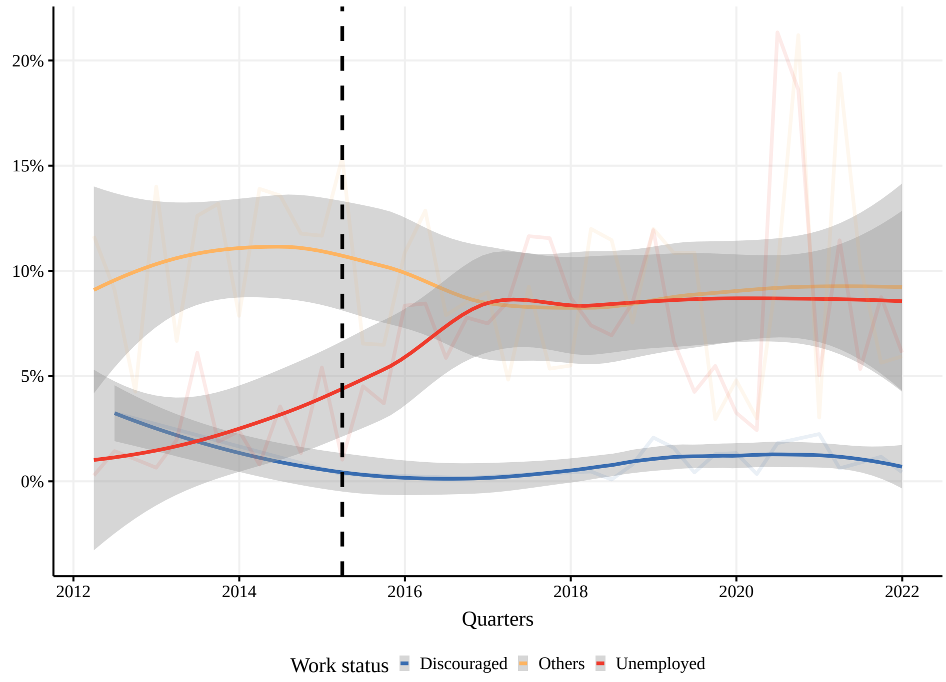
Year	Occupied	Occupied - App driver	Unemployed	Discouraged	Inactive
2012	40.05	48.26	0.85	0.91	9.93
2013	38.19	48.57	3.02	-	10.22
2014	32.52	51.65	3.05	-	12.77
2015	38.59	47.53	4.40	0.07	9.41
2016	36.95	46.58	7.25	0.04	9.18
2017	34.66	48.75	10.12	0.20	6.26
2018	33.09	46.74	8.72	0.86	10.59
2019	26.54	59.42	5.12	1.22	7.70
2020	17.90	62.13	10.58	1.15	8.24
2021	39.55	42.75	7.68	0.57	9.46

Source: Authors own elaboration.

When verifying the composition of occupied, evaluating the portion as app drivers, there is a growing participation of this segment in the middle of the pandemic, rising from 48% in 2012 to around 60% in 2019 and 2020.

Even though this movement has occurred, there is a considerable proportion of employed individuals from other occupations who migrated to app drivers. These represent roughly 10% on average of the transitions made. Furthermore, it is interesting to analyze the movements without the distortion that the massive proportion of the previously occupied generates. Therefore, we have figure 14 below that reproduces the data without this portion. Since the pattern of the data is erratic, we tried to smooth it by estimating an ordinary least square lines to better visualize the trends. In the chart, the growth of the unemployed portion after the entry milestone is evident, in addition to a slight decrease in the Inactive (Others) category. It is noted that the new occupation became attractive, possibly due to the flexibility of entry into the occupation, making it easier for the unemployed to become employed again, even though in an unusual occupation in terms of working hours and formality.

Figura 14 – Proportion of the sample by work status (without employed)



Source: Authors own elaboration.

Turning to the occupied, it is possible to restrict their transitions and look more closely at the occupational position of this portion. Hence, table 5 below gives a closer look. It can be noted that the self-employed still has a high proportion, indicating that, in terms of occupation, the informality of the self-employed may make this transition easier. The informal employed also show slight growth, while the employed with a contract show stability and later decrease, particularly in 2019 and 2020.

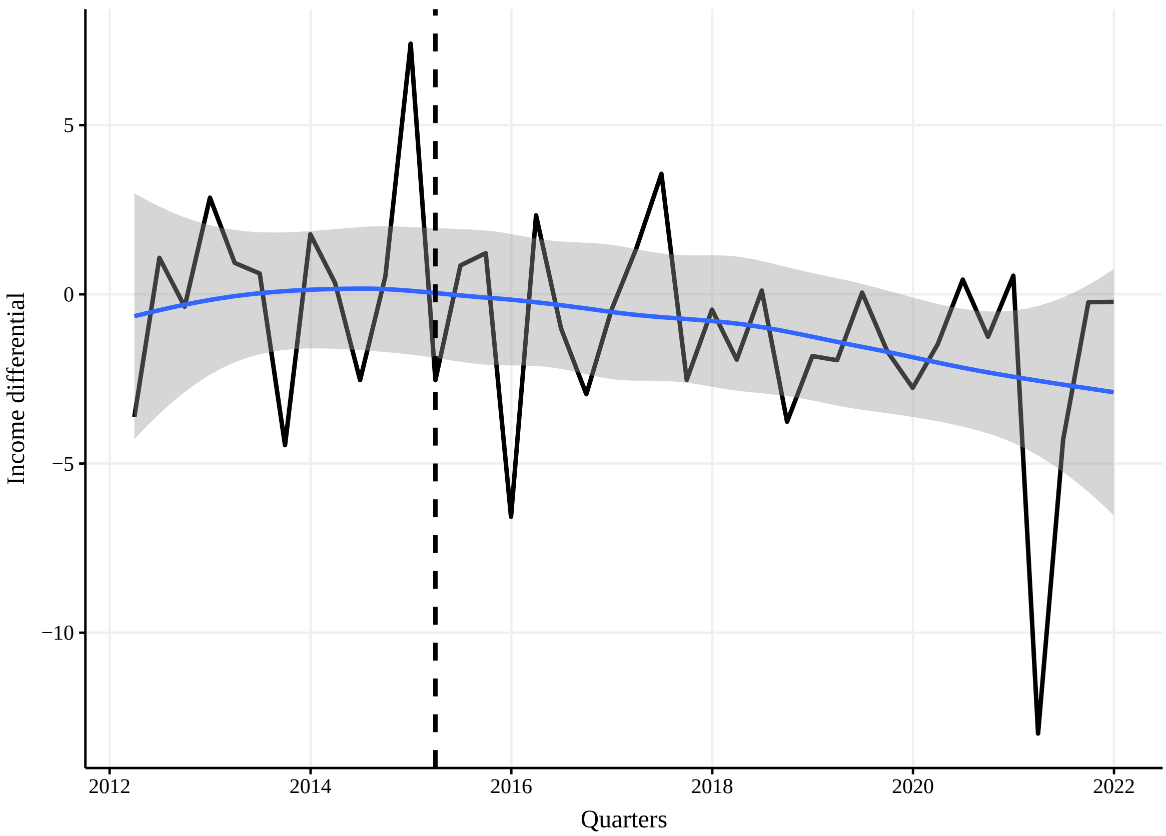
Tabela 5 – Proportion of the sample by occupational position

Year	Formal	Informal	Self employed	SE (private driver)	Employer
2012	15,96	9,41	16,31	54,65	3,68
2013	16,79	8,04	17,08	55,98	2,11
2014	13,70	8,81	14,89	61,36	1,24
2015	19,45	9,6	13,89	55,19	1,87
2016	21,42	9,97	11,47	55,76	1,38
2017	15,78	8,99	15,95	58,45	0,83
2018	15,87	10,07	14,03	58,55	1,48
2019	11,94	6,71	12,04	69,13	0,18
2020	7,40	5,26	9,70	77,64	-
2021	13,19	5,03	26,61	51,95	3,22

Source: Authors own elaboration. Notes: SE refers to self-employed. Annual values calculated from the weighted average of the quarterly values by the sampling weights.

Regarding hourly income, it can be observed from figure 15 below how the income per hour differential shows a stability with a slight increase over the quarters before the entry milestone and, after the apps' entry, proceeds to fall, reaching the negative value of around -2.5 at the end of the series; indicating that, of the occupied in the previous year, all transitioned to the app driver occupation experiencing a decline in income. Altough quarters preceding the apps' entry have a slight positive value, the income differential stays in negative values all the way further.

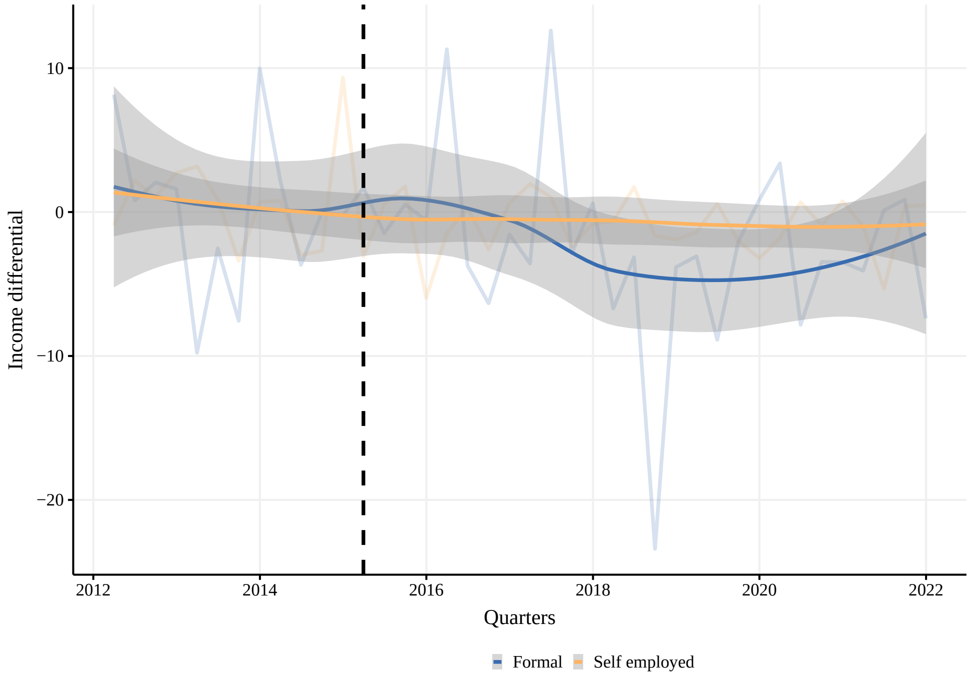
Figura 15 – Income differential when individual is app driver on the fifth visit



Source: Authors own elaboration.

Expanding the analysis to different occupational positions, the graph below disaggregates the income differential for formal and self-employed occupations. Since the sample size is significantly reduced, the analysis is compromised, as indicated by the erratic movements of both segments. The other occupational positions were omitted because their values were so volatile that they compromised the analysis. The chart shows that the decline was mainly due to individuals who were previously in formal occupations. While the self-employed did not show variations over the years, those in formal employment experienced a slight increase in income differential immediately after the apps' entry, possibly capturing a period when the app driver occupation was so competitive that transitioning to an app driver led to income gains. However, after 2017, there is a progressive decline in the income differential.

Figura 16 – Income differential when individual is app driver on the fifth visit by occupational status (Formal and Self employed)



Source: Authors own elaboration.

By annualizing the values, it is possible to construct income measures that represent the average hourly income at the beginning and end of these transitions that are less volatile. Table 6 below presents this exercise, with each row representing transitions made in quarters of one year to the same quarters one year later. Each column contains the initial and final average hourly income values and their percentage variation for each type of transition. The dotted line divides the table entries to mark the entry of the apps in Brazil.

Generally speaking, it is interesting to note that although the final destination is always becoming an app driver, depending on the initial occupational position, the hourly income obtained as a driver changes, especially when comparing those who came from formal occupations to those who came from informal occupations or were self-employed.

Previously formal workers have a higher income level as app drivers than the others; possibly, this difference comes from the ride categories. Since formally employed individuals tend to have higher income levels than those in other occupational positions, they tend to have better cars, which are more likely to be allowed in the more exclusive ride categories (such as the *Comfort* and *Black* categories in the case of Uber). Through these rides, especially in the initial years of app entry when the popular category was not as widespread, this group could have a higher hourly income.

Unlike formal and informal workers, the self-employed were the only ones to have a consistently negative income differential over all the years after the app's entry. Although with mostly negative differentials, formal and informal workers had positive average transitions in terms of income in the years 2016 and 2017. Finally, it is interesting to note that the category that remains as app drivers in the following year shows positive increases in hourly income until the pandemic years, in which there is a decrease; except for the first year post-entry, in which there is a small drop in hourly income. It can be argued that this small drop is due to the entry of app drivers into the evaluated driver occupation, indicating that those who were in the occupation before had a higher hourly income.

Tabela 6 – Annual hourly income and differential by type of transition (App driver in the final interview)

	Formal -> Ridesharing			Informal -> Ridesharing			Self employed -> Ridesharing			Stayer		
	Start	End	Δ (%)	Start	End	Δ (%)	Start	End	Δ (%)	Start	End	Δ (%)
2012 > 2013	R$ 16,3	R$ 18,5	14%	R$ 24,4	R$ 13,4	-45%	R$ 20,6	R$ 21,7	6%	R$ 19,3	R$ 20,7	7%
2013 > 2014	R$ 21,1	R$ 17,9	-15%	R$ 14,2	R$ 13,7	-4%	R$ 15,8	R$ 15,7	-1%	R$ 19,7	R$ 20,2	3%
2014 > 2015	R$ 16,2	R$ 14,9	-8%	R$ 16,7	R$ 16,2	-3%	R$ 16,2	R$ 17,7	9%	R$ 21,1	R$ 22,2	5%
2015 > 2016	R$ 15,4	R$ 15,8	3%	R$ 23,5	R$ 21,6	-8%	R$ 17,1	R$ 15,2	-11%	R$ 21,5	R$ 20,4	-5%
2016 > 2017	R$ 18,1	R$ 17,3	-4%	R$ 11,3	R$ 12,4	10%	R$ 22,8	R$ 16,7	-27%	R$ 18,0	R$ 18,6	3%
2017 > 2018	R$ 16,7	R$ 19,0	14%	R$ 14,0	R$ 16,7	19%	R$ 15,8	R$ 14,1	-11%	R$ 15,0	R$ 15,2	1%
2018 > 2019	R$ 22,4	R$ 14,5	-35%	R$ 14,5	R$ 13,8	-5%	R$ 19,3	R$ 14,9	-23%	R$ 15,9	R$ 16,5	4%
2019 > 2020	R$ 15,1	R$ 12,7	-16%	R$ 12,6	R$ 10,0	-21%	R$ 18,7	R$ 14,5	-23%	R$ 15,2	R$ 14,0	-8%
2020 > 2021	R$ 12,0	R$ 12,0	0%	R$ 12,9	R$ 11,8	-9%	R$ 12,9	R$ 11,7	-9%	R$ 13,3	R$ 13,0	-2%
2021 > 2022	R$ 15,4	R$ 13,2	-14%	R$ 10,9	R$ 10,5	-4%	R$ 13,4	R$ 14,1	6%	R$ 14,4	R$ 12,6	-12%

Source: Authors own elaboration.

Conversely, it is also interesting to evaluate the other direction, the “after”: to which work statuses or occupational positions (if still employed) individuals who initially appear in the PNAD-C survey as app drivers transition? Therefore, the same previous analysis was conducted, now assessing the status of app drivers one year after their first interview in the panel.

As shown in table 7 below, it is evident that app drivers remain employed. Together with the same table from the previous analysis, it is possible to theorize that the occupation of app driver serves as a safety cushion for these workers that is not so much temporary, it could be more permanent than what is tipically expected.

Tabela 7 – Proportion of the app driver destination by work status

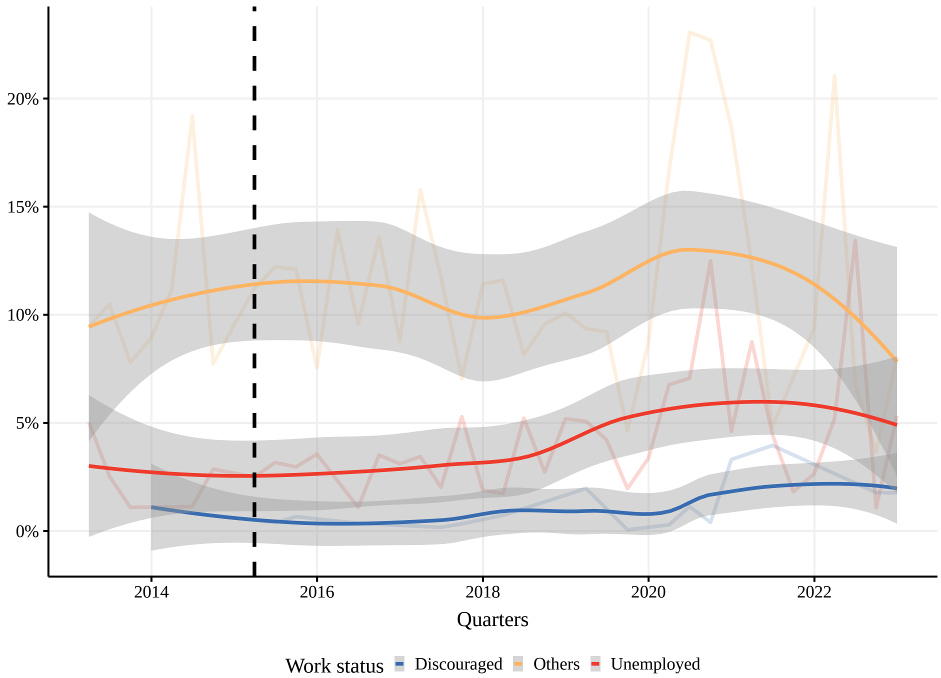
Year	Occupied	Occupied - App driver	Unemployed	Discouraged	Inactive
2013	35.64	52.77	2.14	0.27	9.18
2014	36.59	50.39	1.06	0	11.95
2015	35.12	51.00	3.10	0.24	10.54
2016	28.58	57.81	2.03	0.09	11.50
2017	25.27	60.27	2.96	0.11	11.39
2018	26.38	59.41	3.64	0.63	9.94
2019	28.07	60.01	3.58	0.47	7.87
2020	22.70	47.63	8.05	1.17	20.45
2021	19.44	65.07	5.78	0.58	9.14
2022	34.27	50.36	5.86	1.10	8.41

Source: Authors own elaboration. Notes: Annual values calculated from the weighted average of the quarterly values by the sampling weights.

Naturally, a significant portion of this occupational stability is due to the continuity in the app driver occupation. On average, 55% of employed individuals remained as private drivers before the advent of ride-sharing apps. However, after the introduction of these apps, this proportion increased to an average of 60%.

Removing the the large proportion of employed individuals, we’re able to see more clearly, in a graphical manner, the dynamics of the other work statuses. Figure 17 displays the table graphically, without this segment. Here, unlike the previous analysis where we examined the dynamics preceding the driver occupation, there are no clear changes in the employment status to which the ride-hailing driver transitions.

Figura 17 – Proportion of the sample by work status (without employed)



Source: Authors own elaboration.

Regarding the employed individuals, we see below the dominance of the self-employed category, largely due to the continuous presence of individuals already in the app driver occupation. Before 2015, year of the apps' entry, a greater presence of both formal and informal employment categories is noticeable. After the entry, the self-employed increase, and the formal and informal segments decrease over the years, indicating that app drivers have a different subsequent transition compared to private drivers, who occupied this occupational set alone before the entry of the apps.

Tabela 8 – Proportion of the app driver destination by occupational position

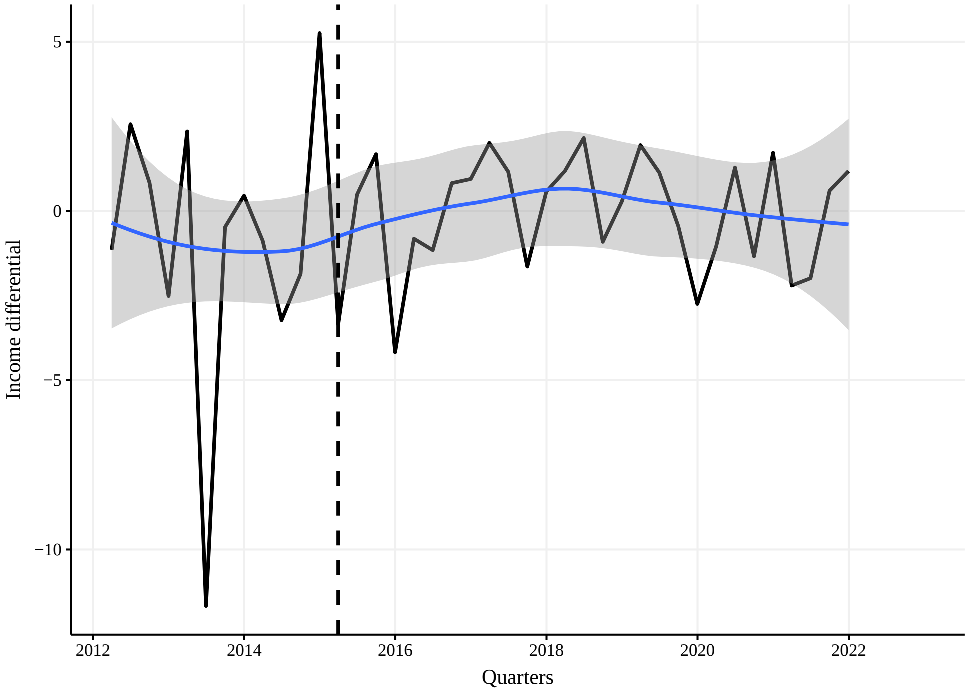
Ano	Formal	Informal	Self employed	Employer
2013	15,8	6,4	74,3	3,5
2014	15,8	9,6	70,4	4,2
2015	10,6	14,1	73,4	1,9
2016	11,0	8,7	79,1	1,2
2017	9,1	5,7	83,8	1,4
2018	9,7	9,1	79,4	1,9
2019	12,3	7,2	79,4	1,2
2020	13,6	5,6	79,4	1,4
2021	7,5	7,0	85,4	0,1
2022	17,2	8,1	72,9	1,9
2023	10,8	8,1	80,0	1,1

Source: Authors own elaboration. Notes: Annual values calculated from the weighted average of the quarterly values by the sampling weights.

The origin and destination analysis reveals similar and complementary findings that provide a deeper understanding of the underlying dynamics. The majority of the drivers originate from the employed segment and continue to remain employed in this sector. Notably, there has been an increase in the number of individuals transitioning from unemployment to becoming drivers. Also, the probability of remaining employed and continuing to work as a driver increases after joining a ride-sharing app.

Regarding hourly income, it can be observed from figure 18 below that the dynamics of the income differential over the years have a flutuation pattern. Here, each value represents the difference between the income that the app driver has in their last interview, one year later, in whatever occupational position they are in, and the income they had in their first interview as an app driver. It is noted that the entry of the apps caused a positive increase in this differential, indicating that app drivers transitioned to better occupations compared to private drivers (the only group in this occupation before the entry of the apps). Given that many drivers remain as app drivers one year later, this increase in the differential may come from the high initial profitability of being an app driver shortly after the occupation's emergence. Nonetheless, this positive trend keeps the income differential positive until 2020, the year of the pandemic, when it turns negative.

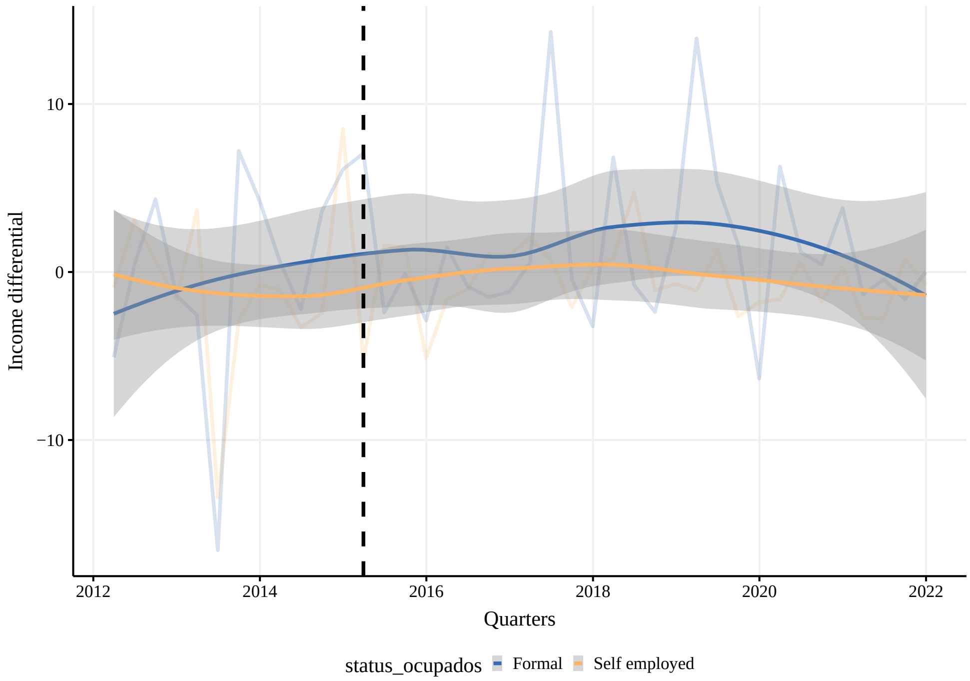
Figura 18 – Income differential when individual is app driver on the first visit



Source: Authors own elaboration.

Unfolding the differential between formal and self-employed, we observe a difference in the level of both. Through the smoothed lines, the premium for landing a formal job compared to a self-employed job is positive, i.e. app drivers that transition to formal occupations tipically have a better income differential compared to app drivers who stays or transition to a self-employed occupation. Also, it can be argued that the self-employed always maintain income differential values below 0, while the formal does not; the latter shows positive values throughout the entire series. In this sense, it is possible to assert that, although few, as previously seen in the distributions, the app drivers who effectively transition to formal occupations do so with an increase in income.

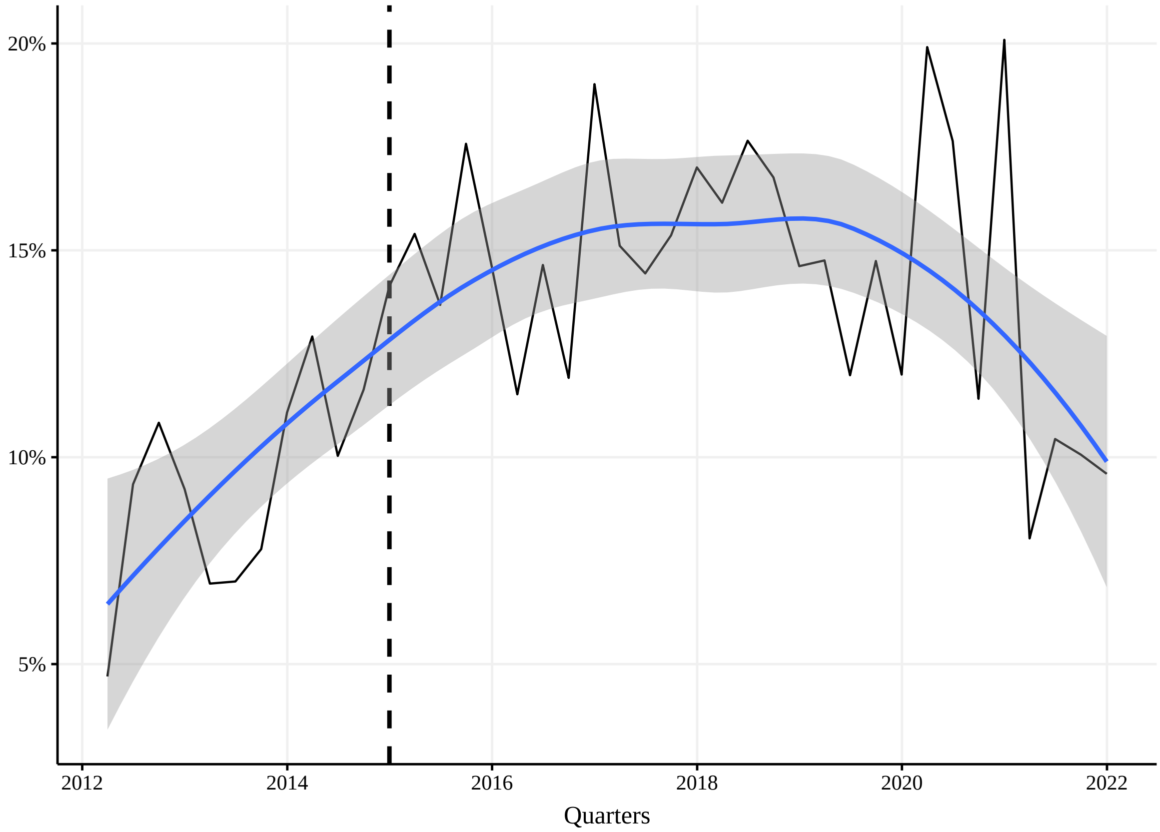
Figura 19 – Income differential when individual is app driver on the first visit by occupational status (Formal and Self employed)



Source: Authors own elaboration.

Another interesting measure to analyze is the proportion of app drivers who remain drivers throughout all five periods. In other words, did the advent of ride-sharing apps lead to greater retention in the private driver occupation? Evaluating figure 20 below, we observe an increase in the proportion of these individuals. It suggests that the shift in occupation to accommodate the new form of work has led to greater retention in this occupation. Conversely, in subsequent years, the Covid-19 pandemic appears to have caused a decrease in this proportion, possibly due to increased income insecurity for platform drivers.

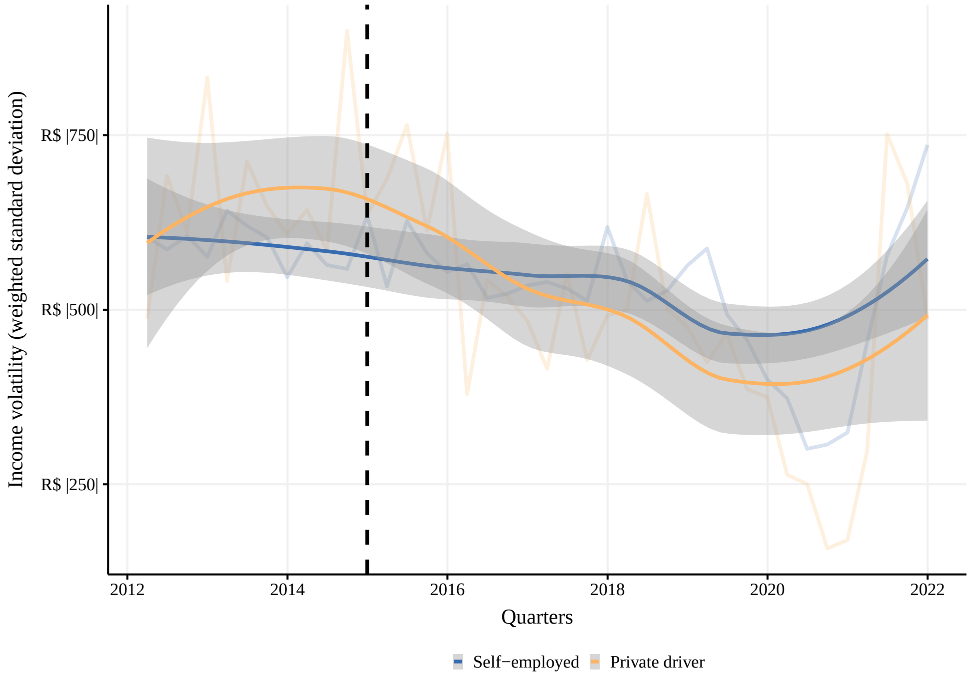
Figura 20 – Proportion of private drivers remaining as such in all five subsequent quarters



Source: Authors own elaboration.

Back to hourly income, it might be interesting to evaluate not only the income differential but also its volatility. To do so, we calculated the standard deviation of income for each individual who remained an app driver for all 5 periods. As a comparison, we calculated the standard deviation for individuals employed as self-employed. Thus, figure 21 below present the standard deviation quarter by quarter for these two groups. Even though very close, the trend lines seem to indicate lower volatility for app drivers after the introduction of the app. This difference persists even during the pandemic years.

Figura 21 – Income volatility by segment



Source: Authors own elaboration.

As in the previous analysis of transitions, here we also produced income differential tables for each type of transition. Generally, the income differential is negative, meaning that app drivers consistently transitioned to lower-income occupations, regardless of the type of occupation they moved to. Since the stayers have a symmetrical configuration similar to the previous table, there were no changes in their values.

Tabela 9 – Annual hourly income and differential by type of transition (App driver in the first interview)

	Ridesharing -> Formal			Ridesharing -> Informal			Ridesharing -> Self employed			Stayer		
	Start	End	Δ (%)	Start	End	Δ (%)	Start	End	Δ (%)	Start	End	Δ (%)
2012 > 2013	R$ 32,9	R$ 14,6	-56%	R$ 14,6	R$ 12,6	-14%	R$ 15,3	R$ 15,8	3%	R$ 19,3	R$ 20,7	7%
2013 > 2014	R$ 18,4	R$ 16,6	-9%	R$ 15,8	R$ 12,1	-23%	R$ 25,4	R$ 16,9	-34%	R$ 19,7	R$ 20,2	3%
2014 > 2015	R$ 16,0	R$ 17,7	10%	R$ 20,3	R$ 15,4	-24%	R$ 20,8	R$ 19,9	-4%	R$ 21,1	R$ 22,2	5%
2015 > 2016	R$ 19,3	R$ 18,2	-6%	R$ 12,8	R$ 11,7	-9%	R$ 18,4	R$ 15,3	-17%	R$ 21,5	R$ 20,4	-5%
2016 > 2017	R$ 14,3	R$ 13,4	-6%	R$ 16,8	R$ 13,3	-21%	R$ 16,3	R$ 14,4	-11%	R$ 18,0	R$ 18,6	3%
2017 > 2018	R$ 14,1	R$ 14,8	5%	R$ 16,5	R$ 15,0	-9%	R$ 18,1	R$ 19,9	10%	R$ 15,0	R$ 15,2	1%
2018 > 2019	R$ 18,8	R$ 15,9	-15%	R$ 12,8	R$ 13,6	6%	R$ 15,8	R$ 18,0	14%	R$ 15,9	R$ 16,5	4%
2019 > 2020	R$ 13,6	R$ 15,9	17%	R$ 14,6	R$ 13,3	-9%	R$ 19,5	R$ 15,3	-21%	R$ 15,2	R$ 14,0	-8%
2020 > 2021	R$ 11,7	R$ 15,0	28%	R$ 8,7	R$ 17,6	101%	R$ 14,0	R$ 12,4	-12%	R$ 13,3	R$ 13,0	-2%
2021 > 2022	R$ 13,4	R$ 13,7	3%	R$ 14,4	R$ 11,5	-20%	R$ 17,2	R$ 14,5	-16%	R$ 14,4	R$ 12,6	-12%

Source: Authors own elaboration.

Finally, in order to provide additional econometric insight into the sociodemographic dimension of the transitions of app drivers to other employment statuses, a multinomial logistic model was conducted to assess statistically significant correlations.

Tabela 10 – Demographic characteristics

		Ridesharing app driver ➔ Occupied	Ridesharing app driver ➔ Unemployed	Ridesharing app driver ➔ Outside the labor force
Gender	Male	Base category	Base category	Base category
	Female	0.34***	0.47	0.27***
Color	White	Base category	Base category	Base category
	Black and Indigenous	1.11	0.63	0.68
Education	Incomplete Middle Education	Base category	Base category	Base category
	Complete Middle Education	1.31	0.20	1.17
	Complete Secondary Education	1.88**	0.23	2.50**
	Complete Higher Education	1.30	0.36	0.54
Age	14 to 25 years	Base category	Base category	Base category
	26 to 45 years	0.92	1.12	1.56
	46 to 65 years	1.14	4.35	2.29
	66 years and +	0.48	29,791***	2.30

Source: Authors own elaboration. Notes: *p<0.1; **p<0.05; ***p<0.01.

The transitions are aggregated as follows:

- Ridesharing app driver $\longrightarrow$ Occupied;
- Ridesharing app driver $\longrightarrow$ Unemployed;
- Ridesharing app driver $\longrightarrow$ Outside the labor force.

Although it is not explicitly showed in the table, the estimated model utilized both the variables listed above and their interactions with a dummy variable indicating the entry of the app in period t in city c. The variables alone are included to ensure that the model accounts for them, aiming not to bias the statistical significance of the interaction by omitting the pure variable. For simplicity, the table above provides only the values of the sociodemographic variables interacting with the dummy.

The base category used is "Stayer" which represents the app drivers who remain as app drivers. The coefficients represent the change in the odds-ratio of the outcome (becoming employed, unemployed, or leaving the labor force) relative to the base category. The significance levels are denoted as follows: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$, and no stars indicate that the coefficient is not statistically significant.

For the gender variable, the male category serves as the base category. For females, the coefficient for transitioning to an occupied status is 0,34, indicating that being female decreases the odds of transitioning from a ridesharing app driver to another occupied status compared to males, and this result is highly significant. The coefficient for transitioning to unemployment is 0,47, which is not statistically significant, indicating no strong evidence that gender affects the transition to unemployment. For transitioning to outside the labor force, the coefficient is significant, at the value of 0,27, showing that being female significantly decreases the odds of leaving the labor force compared to males.

Regarding the color variable, the coefficients for Black and Indigenous are not statistical significance for any transition, indicating no strong evidence that color affects these transitions.

The incomplete middle education category is the base category for the education variable. For this variable, the complete secondary education appears to be the significant segment. The coefficient for staying occupied is 0,42, indicating that having a complete secondary education significantly decreases the odds of staying occupied compared to having incomplete middle education. For transitioning to outside the labor force, the coefficient is 0,26, indicating similar effect for leaving the labor force. Both are significant.

For the age variable, the 14 to 25 years category is the base category. Only the 66 years and older age group appears to have statistical significance. In this group, the coefficient for transitioning to unemployment is 29,791, indicating that being 66 years or older significantly increases the odds of transitioning to unemployment. The other transitions don't have statistical significance. This highly elevated result suggest that the sample size of this segment could be a risk to develop any interpretation.

7.3 Impact evaluation of ride-sharing apps' entry on earnings and worked hours

In this section, we present the results of the DiD model regarding four variables: number of occupieds, labor income, worked hours and income per hour. The results will be presented for the labor market as a whole, for the self-employment and for self-employed drivers in Brazilian capital cities. Since the method requires the division of the cities in group, we present the division associated in the table below:

Tabela 11 – Cities grouped together by quarter of app appearance

Group	Capital
14	São Paulo
15	Belo Horizonte, Rio de Janeiro, Brasília
16	Porto Alegre
17	Recife, Curitiba, Goiânia
18	Fortaleza, Salvador
19	Natal, João Pessoa, Vitória, Florianópolis, Campo Grande
20	Teresina, Maceió, Aracaju, Cuiabá
21	Belém, São Luís, Palmas
22	Porto Velho, Rio Branco, Manaus, Boa Vista, Macapá

Source: Authors own elaboration.

The table 12 provides a summary of the Average Treatment on Treated Effect (ATT) for each variable.

Tabela 12 – Overall summary of ATT's ("simple" aggregation):

	Labor Market	Self Employed	SE - Private Driver
	Number of occupieds		
ATT	9764.048	13.099	2.475
Std. Error	303.476	34.259	3289
95% Conf. Int	[(-585.038) - (604.566)]	[(-54.047) - (80.245)]	[(-3.971) - (8.921)]*
	Income		
ATT	-59.37	20.76	-308.15
Std. Error	52.43	119.11	31.84
95% Conf. Int	[(-162,14) - (43,40)]	[(-212,70) - (254,22)]	[(-370,57) - (-245,73)]*
	Worked Hours		
ATT	-57,23	-10,23	-1,54
Std, Error	48,67	72,13	0,22
95% Conf, Int	[(-154,7) - (36)]	[(-151,6) - (131,1)]	[(-1,97) - (-1,10)]*
	Log Hourly income		
ATT	0,0252	0,0495	0,0172
Std, Error	0,0104	0,0216	0,0522
95% Conf, Int	[(0,0048) - (0,0456)]*	[(0,0072) - (0,0919)]*	[(-0,0851) - (0,1195)]

Notes: The simple aggregation represents a weighted average of all group-time average treatment effects with weights proportional to group size.
*p<0.1; **p<0.05; ***p<0.01.
Signif. codes: '*' confidence band does not cover 0.
Control Group: Not Yet Treated.
Anticipation Periods: 0.
Estimation Method: Doubly Robust

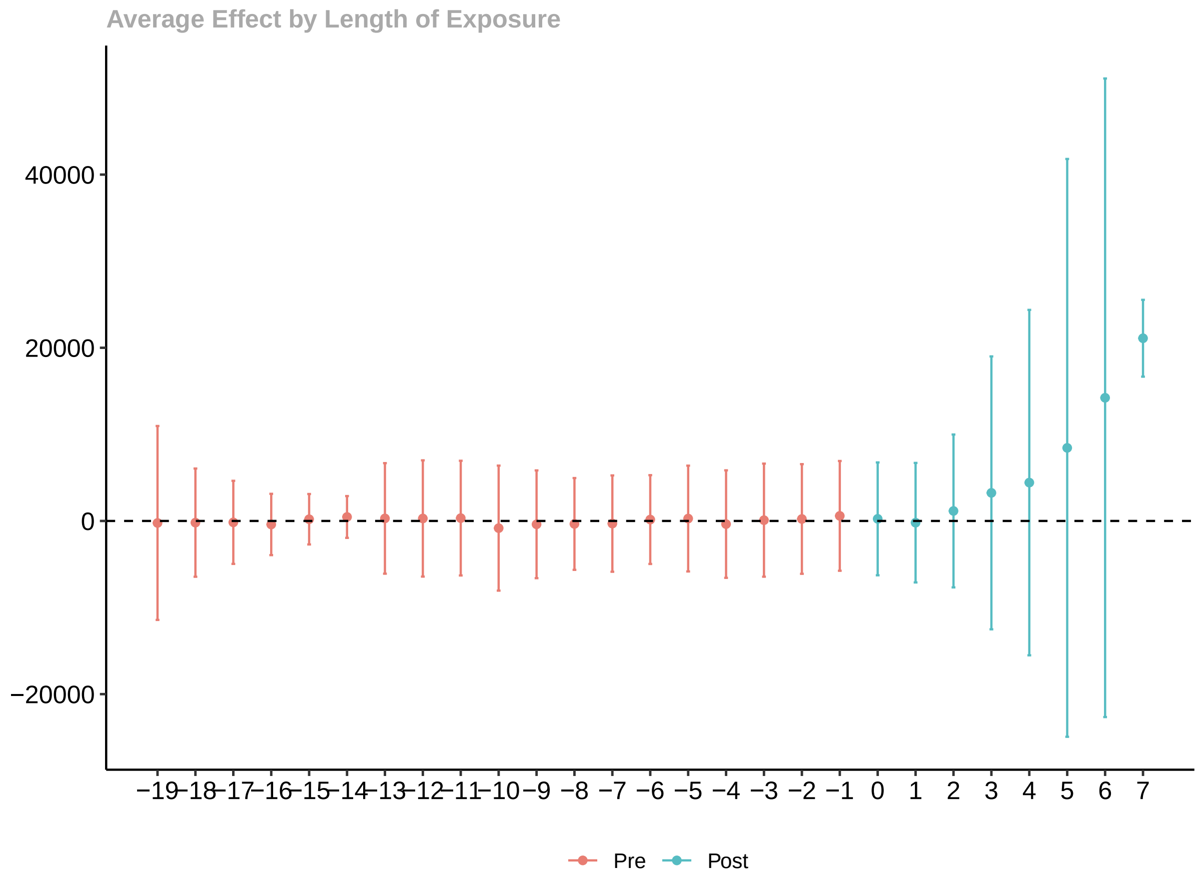
Source: Authors own elaboration.

While the difference-in-difference regression analysis has been conducted on three samples (the labor market as a whole, the self-employed, and app drivers), the most compelling insights arise from examining the sample of the latter.

Focusing on the labor market as a whole is challenging since there are many different jobs and types of employment, making it difficult to compare before and after accurately. Similarly, analyzing the entire self-employed segment is complex, as it includes a wide variety of occupations with different dynamics, which can hide the specific effects of ridesharing apps.

The sample of app drivers provides the most interesting perspective, since the comparison is more direct and clearer: it contrasts the scenario of private drivers before the entry of ridesharing apps (when the ocupation was operated solely as traditional private drivers) with the scenario after the entry of these apps (when the occupation encompases both the traditional private drivers and the app drivers as well). This targeted comparison allows us to isolate the impact of the ridesharing app on their employment and income. Analyzing each variable separately in their respective event study for app driver we verified the result for the total number of the occupieds in the figure below.

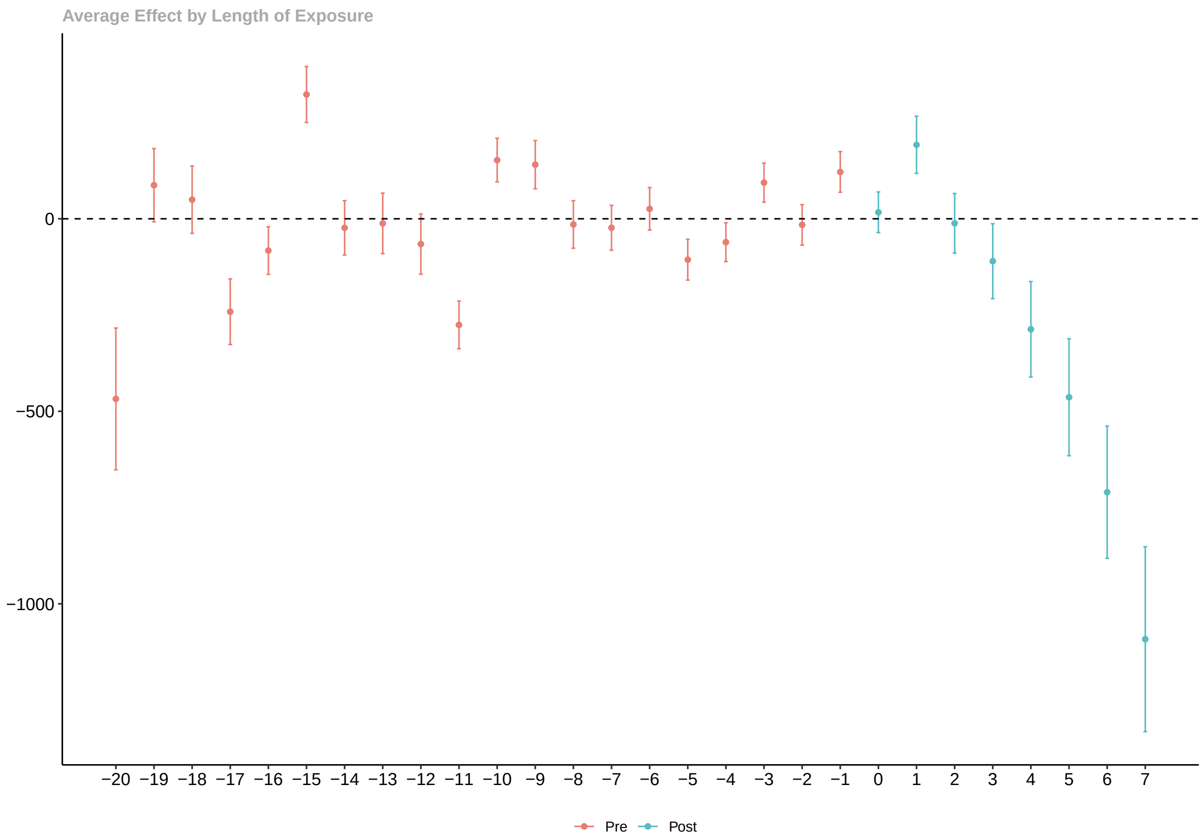
Figura 22 – Average effect of apps' entry on the number of private driver occupied (app driver)



Source: Authors own elaboration.

The graph above represents the ATT dynamically, demonstrates an increase in the number of employed individuals in the last period, indicating a causal effect of the entry of the apps. Regarding the income, figure 23 below presents the results.

Figura 23 – Average effect of ride-sharing apps' entry on income (app driver)

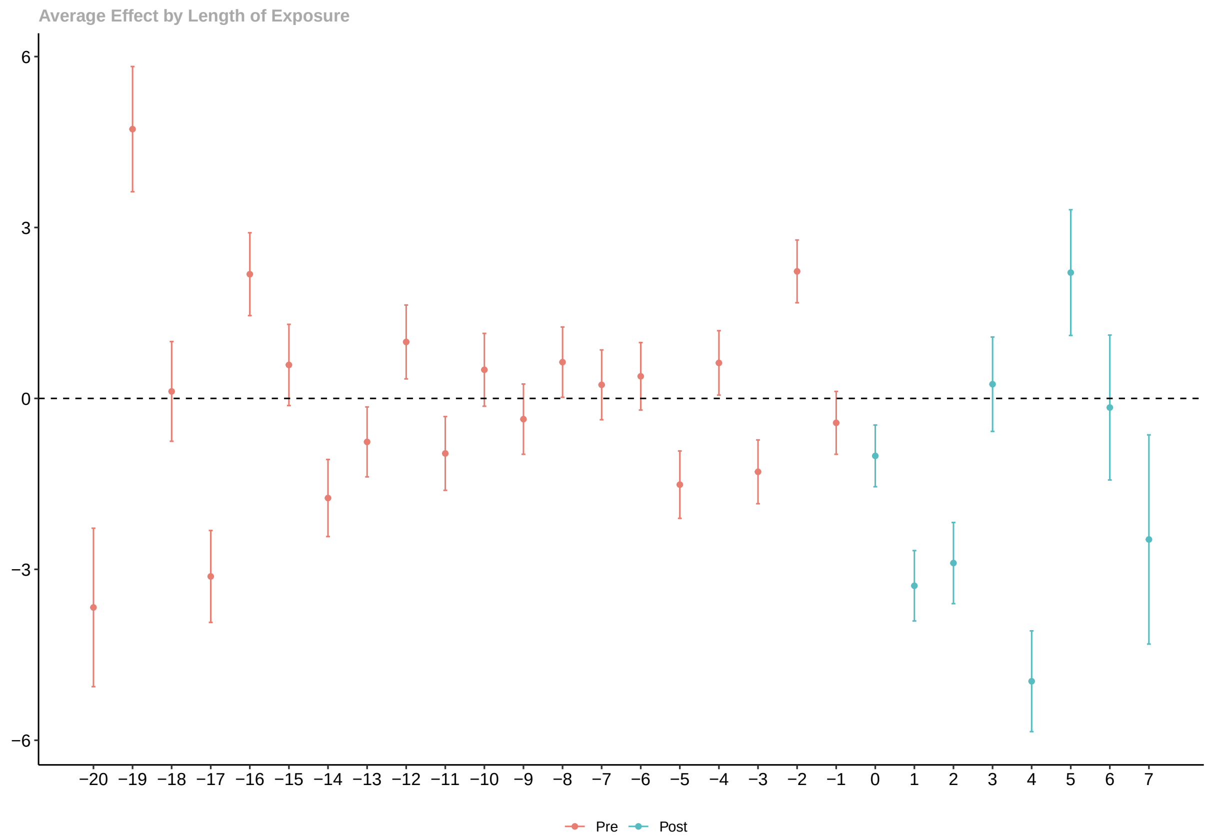


Source: Authors own elaboration.

It can be verified that income presents a post-app entry dynamic, in which there is a high increase soon after the entry and a progressive decline in income after some time. However, it is noted that the results prior to the entry of Uber and 99 are different from zero, potentially indicating a violation of the parallel trends assumption, which suggests that the covariates used were not sufficient to condition the trends.

For the variable of hours worked, we verified the following result:

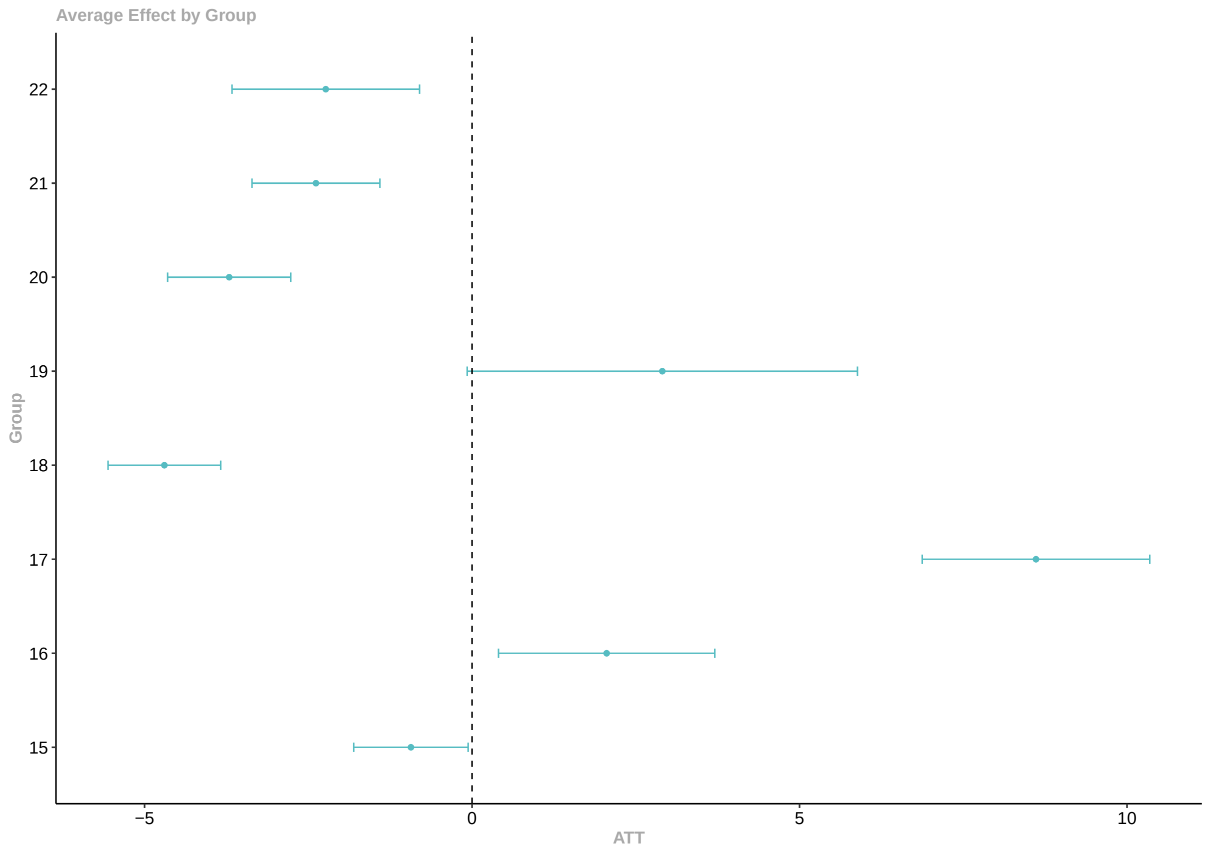
Figura 24 – Average effect of ride-sharing apps' entry on worked hours (app driver)



Source: Authors own elaboration.

Similarly to the previous graph, many results prior to the entry of the apps are different from zero, indicating a violation of the parallel trends assumption. Analyzing the results after the entry, predominantly negative effects are observed, potentially indicating that the apps' entry led to a reduction in working hours. This result may be due to some large variance between the groups. Analyzing group by group, we can see the following result:

Figura 25 – Average effect of ride-sharing apps' entry on worked hours by group (app driver)

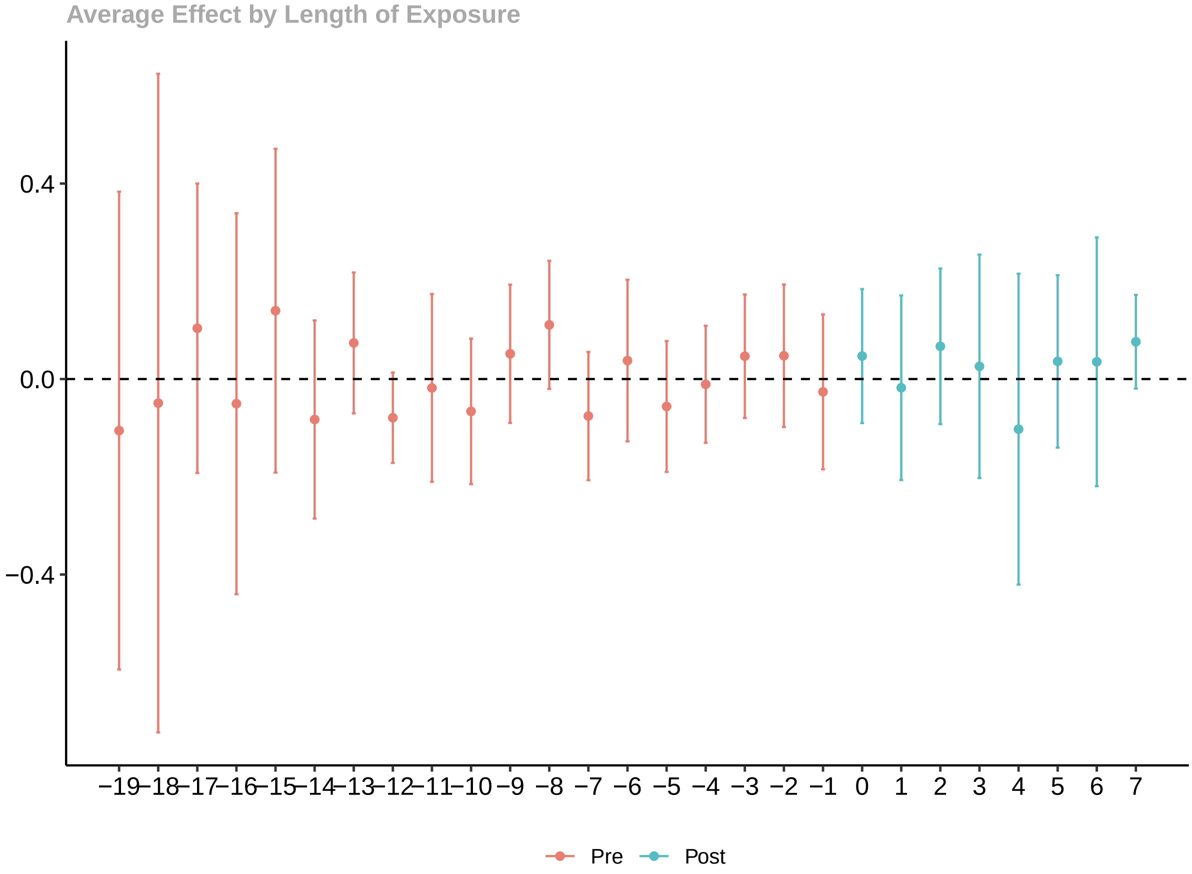


Source: Authors own elaboration.

This result may indicate some dynamics regarding working hours resulting from variations in the opportunity cost of drivers. Perhaps, at the beginning, the supply of drivers was incipient in such a way that the drivers present on the platform obtained substantial compensation, causing many to use the app as their primary source of income. As the supply of drivers grew, the compensation obtained from the app was no longer as substantial, causing the number of working hours to decrease.

At last, the figure 26 despicts the results for the income per hour

Figura 26 – Average effect of ride-sharing apps' entry on log income per hour (app driver)



Source: Authors own elaboration.

Although parallel trends were not a threat in this analysis, the hourly income did not show any sign of variation, indicating that it's not possible to affirm that the introduction of the ridesharing apps significantly impacted the hourly wages of the workers studied.

In general, the estimations can't be viewed as insurance for establish causal impact. Still, there's results that provides interesting insights. Regarding the number of occupieds, it clearly shows an increase, with no variation on the effect before the entry. Regarding the income, the chart shows that after the entry of Uber and 99, there was an increase, which was followed by a progressive decline over time. Additionally, the analysis shows that after apps' entry, there was a reduction in working hours, altough coefficients prior the treatment are volatile (potentially due to a large variance between the groups). The effect on working hours varied depending on the group, with those that adopted ride-sharing occupations earlier seeing a positive effect, and those that adopted it later seeing a negative effect. Looking at the hourly income, it showed no impact.

This dynamic regarding income may be related to the opportunity cost of drivers. At the beginning, the supply of drivers was low, causing drivers on the platform to obtain substantial compensation, making the app their primary source of income. However, as the supply of drivers grew, the compensation obtained from the app was no longer as substantial, resulting of the income. Hourly income showed no change because the drivers adjusted and did less hours of work.

8 RESEARCH LIMITATIONS AND POSSIBLE ADVANCEMENTS

The difficulty in obtaining data related to app drivers from companies, the lack of research on these workers, and the reduced government investment in statistical research as a whole make studying this new occupational model a challenge. This section aims to engage in a reflection regarding these potential limitations and possible research advancements.

Given the absence of clear designation of these workers in the PNAD-C, the chosen occupational set serves only as a proxy and, as previously described, carries limitations. The main limitation is the mandatory joint analysis of app drivers and taxi drivers. This inclusion obscures the entire market dynamics between these two categories, making the calculated measures for this occupation net of this dynamic. A possible line of research to shed light on this issue would be to use question code V4022 in the PNAD-C, which asks about the individual's place of work. Through this question and using the PNAD-C in a panel format, it would be possible to evaluate taxi drivers who are not self-employed (to differentiate from app drivers) and who answered this question as "In a motor vehicle" before the entry of Uber and 99, and compare them with app drivers after the entry. Although the effect of the dynamic found is short, considering that the PNAD-C panel lasts for 1 year, it would be potentially beneficial to shed light on this dynamic. The major difficulty, and the reason it was not implemented in this study, is that the question was only introduced in 2018, severely limiting the sample used in this research.

When analyzing data in a panel study, focusing on a single occupation can pose significant challenges. For instance, evaluating the occupation of app drivers exclusively may introduce biases due to the unique nature of their work schedules. Given that app drivers often have varied and irregular working hours, they are less likely to be available for interviews at home. This unavailability can result in a sampling bias where only those app drivers who are more likely to be at home during survey times are included in the study.

This potential bias suggests that the app drivers who do get interviewed may have different characteristics compared to the broader population of app drivers. For example, the interviewed drivers might work fewer hours, have different income levels, or have varying availability compared to those who are frequently on the road. Such differences can skew the results and provide an inaccurate representation of the overall population of app drivers.

To address this issue, it may be necessary to adjust the sample weights to account for the unique characteristics of this specific occupation. By doing so, we can attempt to correct for the potential biases introduced by the irregular availability of app drivers. This adjustment would involve recalibrating the weights used in the analysis to better reflect the probability of being interviewed for those drivers, thereby providing a more accurate picture of their occupational patterns and experiences.

Recently, IBGE released a specialized survey conducted directly with platform workers, including app drivers[1]. This survey could serve as a valuable reference for statistically correcting the sample weights. By integrating findings from this recent survey, we could adjust the weights to better represent the specific circumstances of app drivers.

However, there are challenges associated with this approach. The IBGE survey captures a snapshot in time, reflecting the current state of platform work. In contrast, our study spans a decade, covering periods both before and after the introduction of ride-hailing apps. Therefore, while the IBGE survey can provide contemporary insights, we must be cautious in applying its findings retrospectively across the entire study period. The temporal differences between the datasets must be carefully considered to ensure that the weight adjustments are valid and do not introduce new biases. While focusing on a single occupation in a panel study offers valuable insights, it also necessitates careful consideration of sampling biases and weight adjustments. By leveraging recent specialized surveys and adjusting sample weights, we can mitigate some of these biases. Nevertheless, it is crucial to remain mindful of the temporal scope of the data and the potential limitations that such adjustments may introduce.

[1] Available at <https://biblioteca.ibge.gov.br/index.php/biblioteca-catalogo?view=detalhes&id=2102035>. Accessed on 06/07/2024.

9 CONCLUSION

The advent of ride-sharing apps such as Uber and 99 has led to the growth of the gig economy and new forms of work in Brazil. Although it has been argued that the low entry costs and worker flexibility increase employment levels, this growth in the gig economy may be associated with the precarization of work. The growth of informal jobs between 2015 and 2018 coincides with the emergence of gig workers and the increase of Uber and 99 presence in the Brazilian cities, which is marked by the significant increase of the self-employed driver. However, a sharp drop in the average labor income of is observed, which may be due to the entry of the ride-sharing apps or/and the economic recession in the country.

In this thesis, we have attempted to analyze the effect of ride-sharing apps' entry into the local transportation market on the labor market. By attempting a three-step analysis, consisting in descriptive statistics, transition analysis and a causal impact assessment, we aimed to investigate both the labor market dynamics resulting from transport apps' entry and it's direct causal impact. In our descriptive statistic, we observe changing in the profile of self-employed drivers with increase of black and secondary level of education workers and a decrease in average hourly earnings.

The transitions analysis reveals various insights. Many drivers were previously employed before transitioning to app driving, and many continue afterwards. A large portion of them stay as an app driver, indicating that this type of occupation is not so temporary like it's usually noticed. Alternatively, could be that the panel duration (1 year) is not sufficient to capture transitions to other types of occupation.

Simultaneously, there was a small increase in unemployed individuals transitioning to app driving after the apps' entry, indicating its capability to function as an income cushion. Regarding income, before app entry, income per hour showed slight increases, but post-entry, it fell to negative values, indicating a general decline in income for those transitioning to app driving. Formal workers transitioning to app driving initially saw income gains, but this gain declined after 2017, while self-employed individuals consistently experienced negative income differentials. The analysis of annualized income transitions shows that formally employed individuals transitioning to app driving have higher income levels compared to informal or self-employed workers, possibly due to better cars eligible for premium ride categories, leading to higher incomes as app drivers.

In our causal impact assessment, the estimations cannot be viewed as definitive evidence of causal impact, yet they provide interesting insights. The number of employed individuals clearly increased with no variation before the apps' entry. Regarding income, there was an initial increase after the entry of Uber and 99, followed by a progressive decline over time. Additionally, the analysis shows a reduction in working hours post-app entry, though coefficients prior to treatment are volatile, potentially due to large variance between groups. The effect on working hours varied: early adopters of ride-sharing occupations saw a positive effect, while late adopters saw a negative effect. This dynamic regarding income may be related to the opportunity cost of drivers. Initially, low driver supply led to substantial compensation, making the app their primary income source. However, as driver supply grew, compensation decreased, resulting in stable hourly income as drivers adjusted by working fewer hours.

Overall, this analysis provided a glimpse into the dynamics and effects involved in the emergence of this new type of occupation. These workers, while similar to informal and self-employed individuals, have a completely different and new work relationship. Although this occupation creates opportunities and income gains for individuals in worse positions or without employment, the continuous maintenance of workers in this new occupation is a warning sign. It is possible that, beyond a short-term positive effect, app drivers may face long-term negative effects, such as difficulties in re-entering the formal labor market, resulting in an undesirable equilibrium. Unfortunately, the limited timeframe of this study is not extensive enough to capture the medium and long-term dynamics involving these individuals. Follow-up research on this category could provide new insights regarding the sustainability of individuals in these positions.

REFERÊNCIAS

AMORIM, B. M. F.; CORSEUIL, C. H. L. *Análise da dinâmica do emprego setorial de 2014 a 2015*. 2016. Accepted: 2016-06-14T14:27:47Z Publisher: Instituto de Pesquisa Econômica Aplicada (Ipea). Disponível em: <https://repositorio.ipea.gov.br/handle/11058/6526>. Cited on page 27.

ANGRIST, J. D.; PISCHKE, J.-S. *Mostly harmless econometrics: an empiricist's companion*. Princeton: Princeton University Press, 2009. OCLC: ocn231586808. ISBN 978-0-691-12034-8. Cited on page 41.

BARBOSA, R. J. Estagnação desigual : desemprego, desalento, informalidade e a distribuição da renda do trabalho no período recente (2012-2019). *http://www.ipea.gov.br*, out. 2019. Accepted: 2020-05-05T14:06:47Z Publisher: Instituto de Pesquisa Econômica Aplicada (Ipea). Disponível em: <https://repositorio.ipea.gov.br/handle/11058/9949>. Cited on page 12.

BOUVIER, M. et al. *Labour market transitions in the time of Covid-19 in Brazil: a panel data analysis*. 2022. Disponível em: <https://www.ie.ufrj.br/images/IE/TDS/2022/TD_IE_015_2022_BOUVIER_RAZAFINDRAKOTO_ROUBAUD_TEIXEIRA.pdf>. Cited 2 times on pages 28 e 39.

CALLAWAY, B.; SANT'ANNA, P. H. Difference-in-Differences with multiple time periods. *Journal of Econometrics*, v. 225, n. 2, p. 200–230, dez. 2021. ISSN 03044076. Disponível em: <https://linkinghub.elsevier.com/retrieve/pii/S0304407620303948>. Cited 2 times on pages 39 e 42.

CARVALHO, S. S. D.; NOGUEIRA, M. O. *Você deve lutar pela xepa da feira e dizer que está recompensado: Evidências da plataformização e a precarização do trabalho no Brasil*. [S.l.]: Ipea, 2023. Cited on page 26.

CHANG, H.-H. THE ECONOMIC EFFECTS OF UBER ON TAXI DRIVERS IN TAIWAN. *Journal of Competition Law & Economics*, v. 13, n. 3, p. 475–500, set. 2017. ISSN 1744-6414, 1744-6422. Disponível em: <http://academic.oup.com/jcle/article/13/3/475/4429543>. Cited 2 times on pages 12 e 25.

CHEN, M. *The Informal Economy: Definitions, Theories and Policies*. 2012. Disponível em: <https://www.wiego.org/sites/default/files/publications/files/Chen_WIEGO_WP1.pdf>. Cited on page 24.

COHEN, P. et al. *Using Big Data to Estimate Consumer Surplus: The Case of Uber*. Cambridge, MA, 2016. w22627 p. Disponível em: <http://www.nber.org/papers/w22627.pdf>. Cited 2 times on pages 12 e 25.

Comissão Nacional de Classificação (Brazil); Instituto Brasileiro de Geografia e Estatística (Ed.). *Classificação Nacional de Atividades Econômicas–CNAE: versão 2.0*. Rio de Janeiro: IBGE, 2007. ISBN 978-85-85539-70-2 978-85-240-3971-3. Cited on page 37.

COSTA, J.; RUSSO, F. M.; HIRATA, G. *Crise econômica e a transição do emprego doméstico no Brasil.* [S.l.], 2019. 47–58 p. Disponível em: <https://repositorio.ipea.gov.br/bitstream/11058/10274/1/bmt_66.pdf>. Cited on page 27.

CURI, A. Z.; MENEZES-FILHO, N. A. O mercado de trabalho brasileiro é segmentado? Alterações no perfil da informalidade e nos diferenciais de salários nas décadas de 1980 e 1990. *Estudos Econômicos (São Paulo)*, v. 36, p. 867–899, dez. 2006. ISSN 0101-4161, 1980-5357. Publisher: Departamento de Economia; Faculdade de Economia, Administração, Contabilidade e Atuária da Universidade de São Paulo (FEA-USP). Disponível em: <https://www.scielo.br/j/ee/a/NqzSQt9ZpV5PMfY78RMGQVd/?lang=pt>. Cited on page 27.

ESTEVES, L. A. Rivalidade após entrada: o impacto imediato do aplicativo Uber sobre as corridas de táxi porta-a-porta. p. 26, 2015. Cited on page 26.

GLASNER, B. The Minimum Wage, Self-Employment, and the Online Gig Economy. *Journal of Labor Economics*, p. 719690, mar. 2022. ISSN 0734-306X, 1537-5307. Disponível em: <https://www.journals.uchicago.edu/doi/10.1086/719690>. Cited 2 times on pages 12 e 25.

HALL, J. V.; KRUEGER, A. B. An Analysis of the Labor Market for Uber's Driver-Partners in the United States. *ILR Review*, v. 71, n. 3, p. 705–732, maio 2018. ISSN 0019-7939, 2162-271X. Disponível em: <http://journals.sagepub.com/doi/10.1177/0019793917717222>. Cited 2 times on pages 12 e 25.

HARRIS, J. R.; TODARO, M. P. Migration, Unemployment and Development: A Two-Sector Analysis. *The American Economic Review*, v. 60, n. 1, p. 126–142, 1970. ISSN 0002-8282. Publisher: American Economic Association. Disponível em: <https://www.jstor.org/stable/1807860>. Cited on page 24.

IBGE. Nota metodológica - Pesquisa Nacional por Amostra de Domicílios Contínua. Accepted: 2024-05-05T14:06:47Z Publisher: Instituto Brasileiro de Geografia e Estatística (IBGE). 2014. Disponível em: <https://ftp.ibge.gov.br/Trabalho_e_Rendimento/Pesquisa_Nacional_por_Amostra_de_Domicilios_continua/Notas_metodologicas/notas_metodologicas.pdf>. Cited on page 35.

IBGE. Nota metodológica - Pesquisa Nacional por Amostra de Domicílios Contínua. Accepted: 2020-01-05T14:06:47Z Publisher: Instituto Brasileiro de Geografia e Estatístisca (IBGE). 2020. Disponível em: <https://ftp.ibge.gov.br/Trabalho_e_Rendimento/Pesquisa_Nacional_por_Amostra_de_Domicilios_continua/Nota_Tecnica/NotaTecnica_Coleta_da_PNAD_Continua_Abril_2020.pdf>. Cited on page 36.

JúNIOR, A. E. T. et al. *Pesos longitudinais para a Pesquisa Nacional por Amostra de Domicílios contínua (PNAD contínua).* [S.l.], 2019. 79–90 p. Accepted: 2020-05-05T14:47:13Z Publisher: Instituto de Pesquisa Econômica Aplicada (Ipea). Disponível em: <https://repositorio.ipea.gov.br/handle/11058/9951>. Cited 2 times on pages 28 e 35.

LEWIS, W. A. Economic Development with Unlimited Supplies of Labour. *The Manchester School*, v. 22, n. 2, p. 139–191, 1954. ISSN 1467-9957. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-9957.1954.tb00021.x. Disponível em: <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-9957.1954.tb00021.x>. Cited on page 24.

LI, Z.; HONG, Y.; ZHANG, Z. An Empirical Analysis of On-demand Ride-sharing and Traffic Congestion. In: . [s.n.], 2017. Disponível em: <http://hdl.handle.net/10125/41152>. Cited 2 times on pages 12 e 25.

LI, Z.; HONG, Y.; ZHANG, Z. The Empowering and Competition Effects of the Platform-Based Sharing Economy on the Supply and Demand Sides of the Labor Market. *Journal of Management Information Systems*, v. 38, n. 1, p. 140–165, jan. 2021. ISSN 0742-1222, 1557-928X. Disponível em: <https://www.tandfonline.com/doi/full/10.1080/07421222.2021.1870387>. Cited 3 times on pages 12, 13 e 25.

MAIA, A. G.; SAKAMOTO, A.; WANG, S. X. HOW EMPLOYMENT SHAPES INCOME INEQUALITY: A COMPARISON BETWEEN BRAZIL AND THE U.S. *Revista de Economia Contemporânea*, v. 23, n. 3, p. e192331, 2019. ISSN 1980-5527. Disponível em: <http://www.scielo.br/scielo.php?script=sci_arttext&pid=S1415-98482019000300200&tlng=en>. Cited on page 13.

MONTEIRO, G. P. É possível gerar estimativas conjunturais a partir de dados longitudinais extraídos da Pnad Contínua? *Revista Ciências do Trabalho*, n. 16, dez. 2019. ISSN 2319-0574. Number: 16. Disponível em: <https://rct.dieese.org.br/index.php/rct/article/view/239>. Cited on page 35.

MOSER, C. O. Informal sector or petty commodity production: Dualism or dependence in urban development? *World Development*, v. 6, n. 9-10, p. 1041–1064, set. 1978. ISSN 0305750X. Disponível em: <https://linkinghub.elsevier.com/retrieve/pii/0305750X78900621>. Cited on page 24.

MOSKATEL, L.; SLUSKY, D. Did UberX reduce ambulance volume? *Health Economics*, v. 28, n. 7, p. 817–829, jul. 2019. ISSN 1057-9230, 1099-1050. Disponível em: <https://onlinelibrary.wiley.com/doi/10.1002/hec.3888>. Cited 2 times on pages 12 e 26.

NAZARENO, L. The Impacts of Ridesharing on Drivers and Job Quality: Evidence from Brazil. *SSRN Electronic Journal*, 2023. ISSN 1556-5068. Disponível em: <https://www.ssrn.com/abstract=4492175>. Cited 2 times on pages 12 e 26.

OLIVEIRA, C. A. d.; MACHADO, G. C. A note on the impact of Uber on Brazilian taxi drivers' earnings. *Revista Brasileira de Economia*, v. 75, n. 3, 2021. ISSN 0034-7140. Disponível em: <https://periodicos.fgv.br/rbe/article/view/79939/80396>. Cited 2 times on pages 12 e 26.

PERO, V.; MACHADO, D. C.; FONTES, A. Informalidad Laboral en Brasil: Análisis de Diferentes Definiciones y Tendencias Recientes. In: RUESGA, S.; ORTIZ, L.; GAY, M. (Ed.). *Diálogos sobre socioeconomía Precariedad laboral, informalidad y mujer. Políticas de cuidados Políticas de cuidados*. Cidade do México: INSTITUTO BELISARIO DOMÍNGUEZ, SENADO DE LA REPÚBLICA: [s.n.], 2022. p. 75–92. Disponível em: <https://www.researchgate.net/publication/366485794>. Cited on page 17.

RANI, S. SOCIO-ECONOMIC ANALYSIS OF UBER TAXI DRIVERS IN KERALA - A STUDY WITH SPECIAL REFERENCE TO ERNAKULAM DISTRICT. v. 6, n. 4, p. 4, 2018. Cited 2 times on pages 12 e 25.

REIS, M.; AGUAS, M. Duraçao do desemprego e transições para o emprego formal, a inatividade e a informalidade. *Economia Aplicada*, v. 18, p. 35–50, mar. 2014. ISSN 1413-8050, 1980-5330. Publisher: Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto da Universidade de São Paulo. Disponível em: <https://www.scielo.br/j/ecoa/a/GpGdHWrPCPCcgsQkcLr7M4g/>. Cited on page 27.

RIBAS, R. P.; SOARES, S. S. D. Sobre o painel da Pesquisa Mensal de Emprego (PME) do IBGE. *www.ipea.gov.br*, ago. 2008. Accepted: 2013-07-25T19:23:53Z Publisher: Instituto de Pesquisa Econômica Aplicada (Ipea). Disponível em: <https://repositorio.ipea.gov.br/handle/11058/1522>. Cited on page 35.

SEDLACEK, G. L.; BARROS, R. P. d.; VARANDAS, S. Segmentação e mobilidade no mercado de trabalho : a carteira de trabalho em São Paulo. *Pesquisa e Planejamento Econômico (PPE)*, v. 20, n. 1, p. 87–104, abr. 1990. Accepted: 2016-01-04T12:02:26Z Publisher: Instituto de Pesquisa Econômica Aplicada (Ipea). Disponível em: <https://repositorio.ipea.gov.br/handle/11058/5849>. Cited on page 27.

SOTO, H. D. *The Other Path: The Invisible Revolution in the Third World*. First edition. New York: HarperCollins, 1989. ISBN 978-0-06-016020-3. Cited on page 24.