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Essays of Platform Work and Changing Workplaces

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ABSTRACT

ESSAYS OF PLATFORM WORK AND CHANGING WORKPLACES

By

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The platform economy provides employment opportunities for many workers, offering benefits such as low entry and exit costs, and flexibility. However, it also represents a contemporary manifestation of nonstandard work, characterized by insecurity and inadequate labor protections. As platforms expand and become more often a full-time job to many, the contradictions between their benefits and precariousness intensify.

Research has clarified the causes and implications of platform work, especially in the context of high-income countries. However, platform work is a global phenomenon, and its impacts are bound to differ across nations. Furthermore, as ridesharing became the poster child of the platform economy, it has received disproportional attention relative to other segments. Still, it is known that rules, outcomes, and experiences vary significantly across platforms.

This dissertation comprises an overview introduction and three independent essays focusing on the platform economy. The first and second essays focus on the impacts of ridesharing on occupational demographics and job quality, taking advantage of the staggered entry of Uber in Brazil as a natural experiment. The first uncover general trends and compares drivers with workers in other arrangements, including formal and informal, while the second zooms in on women in distinct family configurations to investigate whether ridesharing – in

providing a flexible job opportunity – has affected women differently. Findings reveal a surge in the number of people driving as their primary job with a marked decline in earnings and job security trends. Furthermore, the presence of children in the household and urban violence rates affect women's decisions to become drivers differently than men.

The third essay comprises an online experiment and a survey on a freelance platform to investigate United States-based worker preferences, contrasting individuals who rely on the platform as primary and supplemental income sources. Preliminary findings from a pilot study reveal that platform earnings play a significant role in covering essential family expenses, and there is a positive correlation between preference for flexibility and platform reliance. Workers prominently highlight flexibility and business-related benefits as the platform's primary advantages, while identifying elements of precariousness and high fees as major drawbacks.

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BY

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Public Policy in the Andrew Young School of Policy Studies of Georgia State University.

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Dedication

The decision to pursue a doctoral program in a foreign country presented me with numerous challenges that tested me on various levels. I am immensely grateful for the unwavering support of my family, who stood by me throughout every step of this profound intellectual undertaking. Additionally, I extend sincere appreciation to the friends and mentors I encountered along the way. Being surrounded by wonderful people gave me inspiration and strength to embrace this transformative journey.

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Chapter 1: Introduction

Consider one individual who is about to start looking for a job at this moment. Consider all the possibilities available, the skills required, the prospects. Now, take this same individual fifty years back and repeat the exercise. The reader will quickly realize that a lot has changed during this time, and so have the options and strategies that this person would have to consider in both scenarios. Indeed, the world has gone through significant transformations, and these reflected in the labor markets by changing the types of jobs available, the working arrangements, and the organizational structures.

One of the outcomes of globalization, technological developments, and liberalization that occurred during the last decades of the twentieth century was the increase of flexible arrangements and a polarization between "good" and "bad" jobs (Atkinson 1984; Kalleberg 2003; Castells 1996; Weil 2014). The employment change process has been conceptualized from different theoretical lenses but is overall understood as a byproduct of firms searching for cost reductions in the face of increased competition, which translated into a segmentation of the workforce into core/insiders and peripherical/outsiders. Workers in the core are typically employees in charge of essential activities, and outsiders are often subcontracted or outsourced through other firms and/or hired through flexible arrangements. Insider workers usually have higher earnings and leverage benefits, whereas the outsiders face less favorable conditions. In addition to this polarizing trend, the development of automation enabled the substitution of workers performing routine tasks, adding yet another polarization layer (Autor and Dorn 2013; Autor, Levy, and Murnane 2001). Further, as technology evolved, remote supervising enabled the outsourcing of activities previously seen as core to the firm, impacting workers once again

(Goldschmidt and Schmieder 2017; Bernhardt et al. 2015; Dube and Kaplan 2010). As a result, within a few decades, the organization of work has been profoundly transformed:

> The large corporation of days of yore came with distinctive borders around its perimeter, with most employment located inside firm walls. The large business of today looks more like a small solar system, with a lead firm at its center and smaller workplaces orbiting around it. Some of those orbiting bodies have their own small moons moving about them. But as they move farther away from the leading organization, the profit margins they can achieve diminish, with consequent impacts on their workforces (Weil 2014 p.43)

These institutional changes led to a proliferation of flexible and nonstandard work arrangements, which received substantial scholarly attention from the 1990s (Kalleberg 2000; Polivka 1996; Liu and Nazareno 2019). These arrangements include various contracting types, part-time or part-year, temporary jobs, jobs with varying days, times, places of work, and others. While flexibility is beneficial to workers and work-life balance, there are concerns regarding labor protections and job quality. As such, the debate on nonstandard working arrangements portrays a duality between flexibility and insecurity, which tend towards one or another side based on worker and job characteristics. Attention to these issues peaked in the 1990s and early 2000s and then faded away.

However, more recently, the emergence of work enabled by online platforms has contributed to the revival of these debates. Back to the jobseeker from the first paragraph, unlike fifty years ago (or even fifteen years ago), today, someone who is looking for a job has the possibility of quickly downloading an app, filling in a few steps, and being connected to a customer who needs help to fulfill a task. Even though words such as Uber, Lyft, TaskRabbit, and DoorDash have become part of our daily lives, the implications of platform work are not yet fully understood. Surely, much of the flexibility versus insecurity discussion directly applies to platform workers. Yet, some important nuances must be acknowledged.

For example, online platforms have expanded rapidly by making the connection between those buying and selling services an easy and costless process. Consequently, the number of platforms and users (at the seller and buyer end) keeps growing every year (Farrell, Greig, and Hamoudi 2018; Anderson et al. 2021). Further, while ridesharing was a pioneer within the platform world, the platform business model has been expanded to other sectors – a process conceptualized as *uberization* (Fleming 2017; Davis and Sinha 2021; Abilio 2019). Hence, any positive or negative outcomes of platform work are likely to spill over to the economy more broadly.

Algorithmic management is another novelty associated with platform economy, but less present in previous nonstandard jobs. With algorithm management, many of the connections between individuals in platforms are automated and determined through algorithms. Algorithms may determine prices, and details of the task execution (such as routes), sometimes replacing the human interaction between sellers and buyers entirely – as in the case of food delivery. One potential concern regarding algorithm management is that it is usually accompanied by the platform neutrality discourse, which may obscure actual decisions on the rules of the game made by platforms. There are also concerns regarding algorithmic control and how it may affect worker autonomy and well-being (Wiener, Cram, and Benlian 2021; Wood et al. 2019). Noticeably, however, the degree of algorithm management varies substantially across platforms.

Indeed, not all platforms are created equal. The gig economy is continuously evolving, and research suggests variation across platforms on rules, outcomes, and workers' experiences

(Ravenelle 2019; 2017; Vallas and Schor 2020). For example, platforms vary by what they trade, such as *capital* (selling and leasing) and *labor* (transportation and non-transportation) (Farrell and Greig 2016; Farrell, Greig, and Hamoudi 2018). Labor platforms also vary by spatial coverage: in *cloud work*, the task is not location-based and can be done remotely via the internet, whereas in *gig work*, it must be done in a specific location and time. Within cloud work, some platforms distribute tasks to individuals by order of acceptance and for the same payment (crowd work), whereas in others, workers market themselves and are hired based on their skills or portfolio for a negotiated payment (freelance marketplaces) (Schmidt 2017). Table 1 provides a summary of definitions used throughout this dissertation.

Overall, several positive outcomes of platform work are well-established. Evidence suggests that platforms allow workers to complement income, deal with financial volatility, or represent a way out of unemployment (Koustas 2019; Jackson, Looney, and Ramnath 2017; Daniels and Grinstein-Weiss 2018; Manyika et al. 2016; Farrell and Greig 2016). Further, platform workers became essential in helping society navigate through the pandemic when stay-home restrictions were in place. None of these benefits should be underestimated. At the same time, understanding the working conditions faced by platform workers is needed, as job insecurity is a social problem that must be adequately addressed. This is especially important as a growing number of workers report platforms as their full-time job (Anderson et al. 2021; Parrott and Reich 2018; ILO 2016).

The policy challenge is to regulate the platform model without undermining it. The issue of worker misclassification as independent contractors is perhaps one of the most urgent ones (Jackson, Looney, and Ramnath 2017; Harris and Krueger 2015). Platform companies often self-identify as tech companies offering a medium to connect buyers and sellers – the platform. Yet, they are hardly neutral intermediaries. Instead, rules and restrictions imposed on workers may substantially reduce their decision-making power compared to a typical independent contractor while also pushing the risks to them. Again, such a statement varies considerably across platforms. For instance, in freelance marketplaces, workers are often in a much better position to set prices and terms of work than those in transportation platforms.

Table 1. Summary of Definitions

Concept	Definition
Platform work	An umbrella term that incorporates employment relations in which the worker (seller) finds jobs through an electronically mediated platform.
Ridesharing	Ridesharing is a type of platform work in which workers (drivers) provide rides to riders who request them through a platform (e.g., Uber, Lyft, Didi).
Self-employed driver	Self-employed driver is used in this dissertation as a proxy for ridesharing driver.
Gig work	Gig work is defined as an umbrella term to refer to services provided through platforms, in which service provision is constrained to a specific place and time (Schmidt 2017). Examples include rides, delivery, hosting, etc.
Cloud work	Cloud work is defined as an umbrella term to refer to services provided through platforms, in which the task is non-location based and can be performed remotely via the internet. Schmidt (2017) divides cloud work into two broad categories: crowd work and freelance marketplaces.
Crowd work	Crowd work refers to platform work in which the tasks are distributed to individuals by order of acceptance and for the same payment.
Freelance marketplaces	Freelance marketplaces refer to platforms where workers are hired for a specific project based on their skills or portfolio and for a negotiated payment.
Informal work	While there are various definitions of informality, in this dissertation, the term is used to refer to the absence of a formal labor contract, often associated with the lack of labor protections, as defined by the International Labor Organization (2002; 2003)

Still, very few policy attempts to solve this puzzle have become concrete. In 2019, California passed a statute (California Assembly Bill 5 or AB 5) addressing the misclassification issue in the state. However, in 2020, the approval of Proposition 22 granted an exception to app-based platforms, defining some benefits to platform workers but far less than what would have been the case had they been granted employee status (Lake, Kelly, and Beer 2022). More recently, in December 2021, the United Kingdom Supreme Court decided that ride-hailing apps must offer drivers some worker benefits, including access to vacation pay, rest breaks, and minimum wage while they are using the app[1] (Milligan 2021). While the impacts of these policies are still to be determined, they highlight that the discussion is contentious and ongoing.

While platform work posits a regulatory challenge globally, most of the studies to date focused on high-income countries, especially the United States and European countries, and on ridesharing. However, effective policies require a nuanced understanding of how platform work affects workers in their specific contexts and across platforms. As is usually the case, a one-size-fits-all policy is unlikely to work. This dissertation contributes to expanding the knowledge of platform work across settings and platforms.

Chapter 2 explores the staggered entry of Uber in Brazil to observe *changes in the profile of drivers and their employment outcomes compared to other working arrangements in place*. To the best of my knowledge, this study is the first to examine the question in Brazil from a large-scale and quantitative perspective. Being the second largest Uber market globally, Brazil makes an interesting case by default. However, the increasing importance of the driver occupation in the workforce reinforces the need to understand the impacts of ridesharing locally. Furthermore,

[1] Importantly, the worker status is not equivalent to an employee, who are entitled to many other protections.

given the many similarities between Brazil and other middle-income countries, including large contingencies of informal work, findings likely extend elsewhere.

Chapter 3 extends the prior analysis to explore gender dynamics behind ridesharing, building on extensive literature that suggests women have a stronger preference for flexible arrangements. Here, I investigate what characteristics make men and women more likely to drive, with attention to the gendered effects of household composition and city violence. I also focus on how ridesharing has impacted the job outcomes of male and female drivers, and whether it has spillover effects on labor force participation more broadly.

Chapter 4 also revolves around flexibility. Nevertheless, instead of ridesharing, *I focus on a high-skill freelance platform, searching for evidence of worker preference for flexibility*. Preference for flexibility has been claimed as one of the main reasons for engagement in platform work, but empirical evidence is wanting. Taking this assumption for granted may obscure other driver motivations for platform work, including the lack of better opportunities in other sectors. Here, I propose a mixed-methods study combining an online experiment and a survey to observe variations in preferences for flexibility of workers who rely on the platform as their main income source or as a supplementary one, as well as their motivations.

Before concluding this introduction, one last clarification is necessary. While the three essays here focus on platform work specifically, this emerging work arrangement should not be understood in isolation but, rather, as part of a broader trend in labor deregulation and job insecurity. The ability of existing regulations to effectively address the challenges posed by technology and employment in the twenty-first century appears increasingly limited. Significant improvements in the quality of work will require innovative approaches to labor regulation that transcend specific employment arrangements.

Chapter 2: The Impacts of Ridesharing on Drivers and Job Quality: Evidence from Brazil

2.1 Introduction

In the past decade, the world has witnessed the spread of work mediated by platforms, or platform work, pushed by ridesharing. Since then, ridesharing companies, of which Uber was a pioneer, have entered hundreds of markets, and the model has expanded to other sectors. While the implications of platform work will continue to spillover into the broader economy, its consequences are not yet clear.

One of the primary characteristics of the "Uber model" is the low entry costs (essentially having a car and passing a background check) and its flexibility in choosing when and how much to work. As such, ridesharing is an alternative to unemployment and an easy way to supplement income. These characteristics make it a potential job alternative for individuals with constraints that make standard full-time jobs suboptimal choices (Keith Chen et al. 2019). However, there is evidence that platform work is increasingly replacing traditional jobs (Berger et al. 2019) and, in its current form, ridesharing does not conceive of drivers as employees and typically does not provide labor protections and benefits. The absence of protections increases social vulnerability and has translated into debates over the misclassification of workers (Jackson, Looney, and Ramnath 2017; Harris and Krueger 2015).

While ridesharing posits a regulatory challenge globally, assessing the impacts of these reduced protections requires considering the peculiarities of each labor market. For example, in places with larger formalization and labor protections, the expansion of platform work may imply a de-regulation trend, with stronger disruptive impacts in the long run. Distinctly, in areas where there is already concentrated informality, the increase of platform work may not alter the reality of workers substantially, as the model shares similarities with existing informal labor markets and precarious work (Abílio 2020; Myhill, Richards, and Sang 2021; ECLAC/ILO 2021). Whatever the case, the outcomes of platform work must be understood *in context* and compared to other employment arrangements in place.

At this point, several studies have already explored the implications of ridesharing. Among these, most focused on Uber and high-income countries, particularly the United States – especially after the company released data to some researchers (Hall and Krueger 2018; Hall, Horton, and Knoepfle 2017; K.-M. Chen et al. 2020). However, there is still much to know, notably in low- and middle-income countries, where there is a higher concentration of social vulnerabilities and precarious work. Essential questions to these countries – not as salient to the richer world – involve understanding the relationship of ridesharing with informality and where ridesharing drivers stand in the spectrum of work arrangements. To illustrate, interviews with Uber drivers in India reveal emerging forms of informality associated with ridesharing, as drivers who do not own cars end up working for vehicle owners for a fixed monthly pay (Samuel 2020). To the best of my knowledge, such practices have not been noticed in studies covering high-income countries.

This essay's contribution lies in documenting characteristics and changes in the driver's profile and job outcomes in Brazil. Besides being the second largest labor market for Uber globally (Uber 2020), Brazil makes an interesting case study given its similarities with several middle-income countries, including its elevated levels of inequality and polarized labor force between formal and informal. To understand drivers in context, I contrast their demographics and job outcomes (earnings, hours of work, and contributions to social security) with three groups of workers: formal workers, informal workers, and other self-employed (non-drivers). Not self-employed are included as a group of interest, likely affected by the ridesharing industry, but not as a pure control. The choice of such categories intends to build a dialogue between my results and niches of the literature that compare ridesharing with the taxi industry and self-employment, and which discusses gig work as a new face of informality.

The staggered entry of Uber in Brazilian cities provides a natural experiment opportunity to assess the effects of ridesharing. I define self-employed driver as a proxy for ridesharing drivers based on the spike in this arrangement observed following Uber's entry. Data comes from the Brazilian Continuous National Household Sample Survey (PNADC). The paper is structured in two sets of analyses. First, staggered difference-in-difference regressions allow observing changes in the demographic profile and job outcomes of drivers over time as compared to other workers. Second, I take advantage of the rotating panel component of PNADC – which interviews households for five consecutive quarters – and reduce the sample to a panel. I keep in the sample only the workers for whom there was at least one interview before and after Uber's entry and carry an individual fixed-effects analysis to study job transition patterns.

Results show a spike in the number of individuals working as self-employed drivers following Uber entry. Although there is an increase in self-employed driving as both a primary and secondary job, it seems to be replacing traditional employment in most cases. Further, as the number of drivers grew, the driver demographic profile changed, for example, by increasing shares of high-educated workers. Simultaneously, there has been a steady decrease in the earnings of self-employed drivers and subscriptions to social security as compared to all other groups of workers. Drivers also work fewer hours in the post-ridesharing period, although still having longer schedules than the average worker in other arrangements. Finally, results from the panel analysis suggest that self-employed driving has turned into an important alternative for some individuals, especially the unemployed, but not necessarily a long-run one, as the probability of *remaining* in this arrangement across quarters has declined in the post-Uber period. Overall, results show that self-employed drivers are increasingly facing lower pay and higher insecurity, and these cannot be explained by changes in the drivers' demographic profile. While the documented trends may reflect market adjustments to an increased supply of drivers, they are allowed by ridesharing companies' policies and the absence of regulations.

This essay is organized into eight sections following this introduction. Section 2.2 describes the ridesharing entry in Brazil and where drivers stand in the country's regulatory context. In section 2.3, I provide a brief overview of the literature on the uses of ridesharing and drivers' job outcomes. Sections 2.4 and 2.5 discuss the data and empirical strategy. Results are introduced in sections 2.6 and 2.7, and robustness checks are provided in section 2.8 and 2.9. Finally, I discuss the results and their implications in section 2.10.

2.2 Institutional Context

2.2.1 Uber in Brazil

While there are currently several ridesharing companies operating at the national and local levels in Brazil, Uber was the pioneer and remained the dominating one, being the preferred app for 70 percent of consumers, followed by 99Pop (Didi) with 20 percent in mid-2021.[2] As such, I rely on Uber's history as a benchmark for understanding how ridesharing developed in the country.

Uber was launched in Brazil in June 2014, in Rio de Janeiro during the World Cup, and kept a timid expansion until the end of 2015 to four other cities (Sao Paulo, Belo Horizonte,

[2] 99Pop was launched in Brazil in 2016. Later, it was acquired by the Chinese Didi, Uber's main competitor. In 2019, Uber's market share worldwide was 37.2 percent, followed by Didi with 32.4 percent (Statista 2022a; 2022b).

Brasilia, and Porto Alegre). Since then, the company has aggressively expanded, being present in over 500 cities by the end of 2020.

Brazil is the second largest Uber market globally, behind the United States. In August 2020, one million out of the 3.5 million Uber drivers worldwide were in Brazil, as well as 22 million out of the 101 million users (Uber 2020). With such impressive numbers, Brazil makes an ideal case for studying the socioeconomic implications of the ridesharing model to drivers and workers, with potential lessons to be taken to other places.

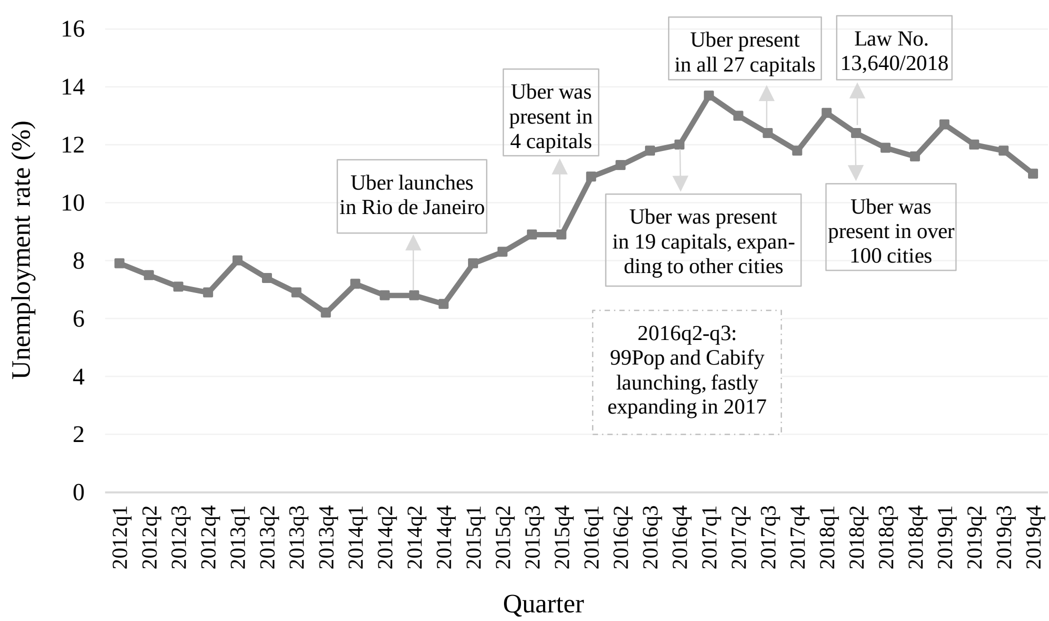

Figure 1. Unemployment Trends and Uber's Entry in Brazilian Capitals

Source: Author's Calculation from IBGE's Quarter PNADC 2012-2019 series.

It is noteworthy that Uber's launch in Brazil coincided with the beginning of a prolonged economic recession with peaking unemployment (Figure 1). Such a timing parallels the United States case, where Uber began to operate in 2010 – the aftermath of the Great Recession. In recessive contexts, Uber becomes an especially attractive alternative for those facing economic stress – and who have an available car. However, family vehicle ownership rates in Brazil are around 50 percent (IBGE 2020), much lower than the above 90 percent in the United States (US Census Bureau 2019). As such, if the Uber opportunity was, *in principle*, available to most families in the United States, in Brazil, it was an alternative to the richer ones. Of course, this restriction was relaxed over time once arrangements facilitating the rent of vehicles for ridesharing drivers became an option.[3]

Similar to other parts of the world, the ridesharing growth in Brazil was followed by significant push-back – especially from the taxi industry – and by conflicting responses across the local level. Although not regulated, ridesharing was not an illegal activity in principle. However, responses at the local and state levels varied, and some prohibited it. An initial solution to the controversies came in March 2018, when the Federal Government passed a law that regulated ridesharing (Law No 13,640/2018). Since then, the conflict with the taxi sector has softened, and the ridesharing model expanded to other sectors (e.g., delivery and services) and modes of transportation (e.g., bikes, motorcycles, and buses).

However, the regulation did not clarify all sensitive points, including the workers' status, which is a matter of discussion worldwide. Ridesharing companies claim to be tech start-ups selling a service to drivers – the platform – in exchange for a fee. In the eyes of these companies, drivers are independent contractors rather than employees. Opponents of this idea emphasize the considerable power of "intermediary" companies in deciding who can use the platform and at which prices and conditions (Jackson, Looney, and Ramnath 2017; Harris and Krueger 2015).

[3] There is evidence that vehicle ownership is a significant factor positively affecting driver's earnings in India (Samuel 2020). In Brazil, anecdotal evidence from news venues and ridesharing-related blogs discusses the rental option as one profitable possibility for those driving "enough" hours (even for those who own a car), especially as the maintenance costs remain a responsibility of the rental company.

While this matter is not solved from a regulatory standpoint, drivers' lawsuits against ridesharing companies continue to pile up.

2.2.2 Labor Protections, Formality, and Informality

In contextualizing the employment status discussion in Brazil, one must acknowledge the duality between formality and informality. Of note, there is no unique definition of informality that applies everywhere, which requires some clarification. *Informality here refers to the absence of a formal labor contract, often associated with the lack of labor protections*.[4]

In Brazil, since 1943, the formal employee status (aka. having a formal labor contract) assures workers extensive labor rights and protections, including overtime pay, sick leave, maternity and paternity leave, paid vacation, unemployment insurance, advance notice (in case of layoffs), an additional thirteenth salary at the end of each year, retirement plan, and others.[5] Costs to ensure these benefits are covered by mandatory contributions from workers *and their employers* to the Brazilian Social Security Institute (INSS). In contrast, workers who do not hold formal ties with their employers end up in informal arrangements, lacking all such protections. Informality in Brazil is estimated at 40 percent, with even higher figures for women, the low-educated, and the black population, similar to other countries in Latin America and the Caribbean (Abramo 2022).

Informal workers can contribute individually to the INSS to become formalized and entitled to social protections and retirement benefits, in which case they will *bear the costs of*

[4] In 2002, the Seventeenth International Conference of Labour Statisticians (ICLS) and the International Labour Organization proposed a broad definition of the informal economy, which includes the informal sector (production units/enterprises), and the and informal employment (jobs/workers) (International Labor Organization 2002; 2003). In this definition, informal employment relates to the unprotected status of workers, regardless of whether they work in a formal or informal enterprise.
[5] Law No 5,452/1943.

such contribution entirely. Notably, *the individual contributor option does not distinguish between workers who resemble formal employees and self-employed workers who operate in a solo-entrepreneur logic in an informal (not registered) business*. Self-employed workers operating as a business may seek formalization and register it as a legal entity, in which case social security contribution becomes mandatory[6]. Thus, in this context, social security contribution rates provide a direct measure of formalization.

In the Brazilian setting, ridesharing drivers are at the edge between formality and informality. When understood as workers without appropriate job contracts, they fall within informal, unprotected arrangements.[7] If understood as independent contractors or microentrepreneurs, they also fall within informal unprotected arrangements. Hence, *unprotected or informal is the default condition*. In both cases, drivers *may seek formalization* through the individual contributor option or formally registering as a business. Subscription to social security is, then, also a proxy for labor protections.

The problem here is clear: while drivers could take either route to assure social protection, there is no assurance that they will, and an unprotected labor force is costly for countries, especially in the long run. In the background (and beyond Brazil), this grey zone reflects the inadequacies of current regulatory labor frameworks in the face of an expanding employment model. The challenge posed to countries lies in "establishing and protecting the social and labor rights of workers, while at the same time harnessing the opportunities that new technologies provide for both workers and consumers" (ECLAC/ILO 2021, p.41).

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[6] Since 2010, there is a legislation in place that allow individual micro-entrepreneurs to registry their business in a low-cost and simplified way (online). The legislation aims at facilitating business registration to increase formalization and simplify compliance with the Brazilian complex tax legislation. Registration as an individual micro-entrepreneur is, therefore, one way to formalizing and assessing social protection benefits.

[7] Note that this definition of informality does not relate to whether these workers pay due income taxes.

2.3 Literature Review

2.3.1 The Uses of Ridesharing

Why do people end up driving for app-based platforms? Answering this question allows one to assess the underlining conditions that explain the growth of this kind of arrangement and its broader implications. This section builds on prior studies on Uber and ridesharing, mainly focused on high-income countries.

Ridesharing is frequently a supplementary income source. In one of the first studies, Hall and Krueger (2018) found that most United States Uber drivers (about 80 percent) relied on the platform to complement other full- or part-time employment and as a medium-term activity. Echoing this picture, M. K. Chen et al. (2019) found that most drove for Uber for fewer than 12 hours per week. In these studies, the variation in work hours throughout days and weeks indicates drivers' utilization of real-time schedule flexibility. Indeed, M. K. Chen et al. (2019) estimate that much of the drivers' surplus stems from the flexibility itself, such that constraints to it would require high compensation differentials not to push drivers out.

The role of driving as a supplemental income is not negligible. For example, Farrell, Greig, and Hamoudi (2018) observed that 58.3 percent of families generating platform income during a year received earnings from transportation platforms in three or fewer months of that year. In these months, the platform earnings represented more than half of the total take-home income in 2018 – down from about 80 percent in late 2012. By the same token, Nian, Zhu, and Gurbaxani (2021) estimated a reduction of 3.3 percent in quarterly personal bankruptcy filings in the United States following Uber's entry.

Simultaneously, there is increasing evidence that ridesharing replaced traditional employment and became the primary income source for many workers. In some cases, this trend seems to result from workers' preferences. In London, for instance, Berger et al. (2019) observed that most drivers transitioned to Uber out of low-paid blue-collar and services jobs and only a negligible share out of unemployment (2 percent). Uber became the primary source of income for about 75 percent of the drivers, who seem to have switched jobs searching for autonomy and schedule flexibility.

In other contexts, ridesharing seems to be an alternative to unemployment instead of a decision to switch jobs. Parrott and Reich (2018) explain that the driver profile in the United States has changed substantially over time. Rather than part-time drivers who value flexibility, they observe that, in New York City, most app-based drivers (60 percent) were full-time workers, of which roughly 20 percent drove for fifty or more hours per week, and many of whom undertook risky capital investments in the vehicles they acquired for driving for passengers. Similarly, based on semi-structured interviews, Valente, Patrus, and Córdova Guimarães (2019) identify that in a Brazilian capital (Belo Horizonte), Uber driving is often an alternative to unemployment rather than a search for temporary and flexible work to supplement earnings. Moreover, in Latin America and the Caribbean, ridesharing is often a full-time option for workers who cannot find a job elsewhere, especially immigrants (ECLAC/ILO 2021).

Whether driving is the main or a supplementary income source is a determinant of drivers' subjective experience in the platform, a finding that extends to the gig economy beyond ridesharing. Those who rely on platforms to supplement a steadier stream of income typically have better perceptions of job quality and higher satisfaction than those who need the money to cover basic living expenses (Schor et al. 2020; Dunn 2020; Myhill, Richards, and Sang 2021; Berger et al. 2019). In this regard, at least part of the story seems to be explained by the fact that workers using platforms as a second job are more likely to be entitled to labor protections through their other employers (Schor 2020).

2.3.2 Job Outcomes

Conflicting findings extend beyond worker motivations to become drivers. On the one hand, several studies identify that platform drivers have higher earnings than other workers. During the early years of Uber, Hall and Krueger (2018) estimated that Uber drivers earned at least as much as taxi drivers and chauffeurs, and in many cases more, while working fewer hours. These increased earnings seem to originate from the real-time use of flexibility, in which drivers learn to take advantage of fare raises/surges (Hall, Horton, and Knoepfle 2017). By taking advantage of the Uber model, drivers earn more than twice the surplus driving for Uber than they would have obtained in less-flexible arrangements (M. K. Chen et al. 2019).

In contrast, other studies portray less optimistic perspectives. For example, London Uber drivers' earnings are similar to other low-paid jobs (Berger et al. 2019). Likewise, Daniels and Grinstein-Weiss (2018) show that while Uber reduced income volatility, it also reduced the overall take-home pay for low-income families in metro areas in the United States. Additionally, part of the driver's earnings is necessarily consumed by vehicle expenses – which in other arrangements would typically be an employer's responsibility (Berg and Johnston 2019; Wang and Smart 2020). There is evidence of differences between income advertised by ridesharing companies (Uber and Lyft) versus more realistic earnings before and after expenses, which in many cases do not even meet the minimum wage (Henao and Marshall 2019). In Latin America and the Caribbean, the relative earnings of drivers compared to other workers vary by country but usually tend to become lower once the unpaid time is accounted for (ECLAC/ILO 2021).

Ridesharing may also generate spillover effects to other workers, among which taxi drivers are perhaps the most directly affected. Here, evidence is also mixed. Berger, Chen, and Frey (2018) found a decline in taxi's hourly earnings of about 10 percent following Uber's entry across 50 United States metropolitan areas, without any effect on taxi labor supply. Distinctly, a study by Kim, Baek, and Lee (2018) in New York City found that, while there had been a dispersion of taxi drivers beyond Manhattan, taxi earnings, trips, and occupancy rates were not significantly affected by Uber entry. However, other studies focused on Brazil and the United States point to reductions in the number of rides in cab-hailing companies, especially in large cities (Resende and Lima 2018; Wang and Smart 2020).

2.4 Data and Research Questions

Overall, the literature review uncovers that while we already know much about platform drivers, the findings seem to change across places and over time. Regarding Brazil, studies carried out so far suggest some nuances, although most focused on local settings and qualitative methods, preventing inferential conclusions. In the present study, I build on the findings from this literature while pushing the frontier to a larger scale to answer three main questions. First, I study changes in the self-employed driver profile following the Uber rollout. Understanding such a change allows for identifying demographic groups that benefited from the novel arrangement, as well as those who were potentially pushed out of the profession. Second, I investigate changes in job outcomes of self-employed drivers compared to workers in other arrangements. Job outcomes include usual monthly earnings and hourly earnings[8], usual weekly hours worked, and

[8] Hourly earnings were calculated as usual monthly earnings divided by 4.5 weeks times the number of hours usually worked on a week: $\frac{usual\ monthly\ earnings}{4.5 * usual\ weekly\ hours\ worked}$. Earnings of private workers were adjusted to account for the thirteenth salary and one third of a salary for vacation.

social security contributions (dichotomous). Additionally, based on job transitions from a panel of workers, I investigate what type of opportunity ridesharing represents in the Brazilian context by studying the probabilities of individuals becoming self-employed drivers given their prior job status (e.g., employed, unemployed, out of the labor force).

The Brazilian Continuous National Household Sample Survey (*Pesquisa Nacional por Amostra de Domicílios Contínua* – PNADC) comprises the main data source. PNADC is a nationally representative survey produced by the National Institute for Geography and Statistics (IBGE), containing detailed information on the labor force and other topics. PNADC is the main household survey in Brazil, heavily used by the government and researchers. Quarterly data from PNADC provides metropolitan and municipal identifiers for individuals living in capitals or the Federal District, and metropolitan areas containing these.[9]

The study leverages the staggered entry of Uber as a natural experiment. Necessary information for the exact date came from a one-by-one search on the Uber blog and other local news sources, similar to Barreto, Silveira Neto, and Carazza (2021). The period of analysis ranges from 2012 to 2019, in which Uber's rollout occurred from the second quarter of 2014 to the last quarter of 2017 (Table A1 in Appendix A). Areas that are nonidentified (and cannot be assigned with a treatment date) were dropped. Therefore, the sample includes roughly 2.2 million employed individuals living in one of the 26 capitals and the Federal District and their respective metropolitan areas (representing 48.6% of the Brazilian employed workers), aged 21 to 75 (the minimum age to work as an Uber driver and the mandatory retirement age for public and private

[9] Quarterly data from PNADC provides microdata at the following geographic levels: metropolitan areas *containing states' capitals and the Federal District*, capitals, other (nonidentified) metropolitan areas in each state, and rural areas. Since metropolitan and municipal identification is only available for individuals living in either capitals or metropolitan areas containing capitals, this study focuses on these.

employees in Brazil). The military, statutory workers (mostly public servants), employers, and unpaid workers in family businesses were excluded from the sample.

PNADC is structured as a rotating panel of households, in which each household is interviewed for five consecutive quarters and then dropped out of the sample. Most of the analysis herein relies on a pooled cross-section of quarterly PNADC from 2012 to 2019. However, the last identification strategy leverages a rotating panel structure, as discussed next.

2.5 Identification strategy

2.5.1 Self-Employed Drivers and Comparison Groups

Self-employed driver (occupation 8322: driver of automobiles, taxis, or pickup trucks) is a proxy for ridesharing drivers. As illustrated in Figure 2, an increasing trend in this occupation follows Uber's entry in Brazilian capitals, making it a compelling proxy.

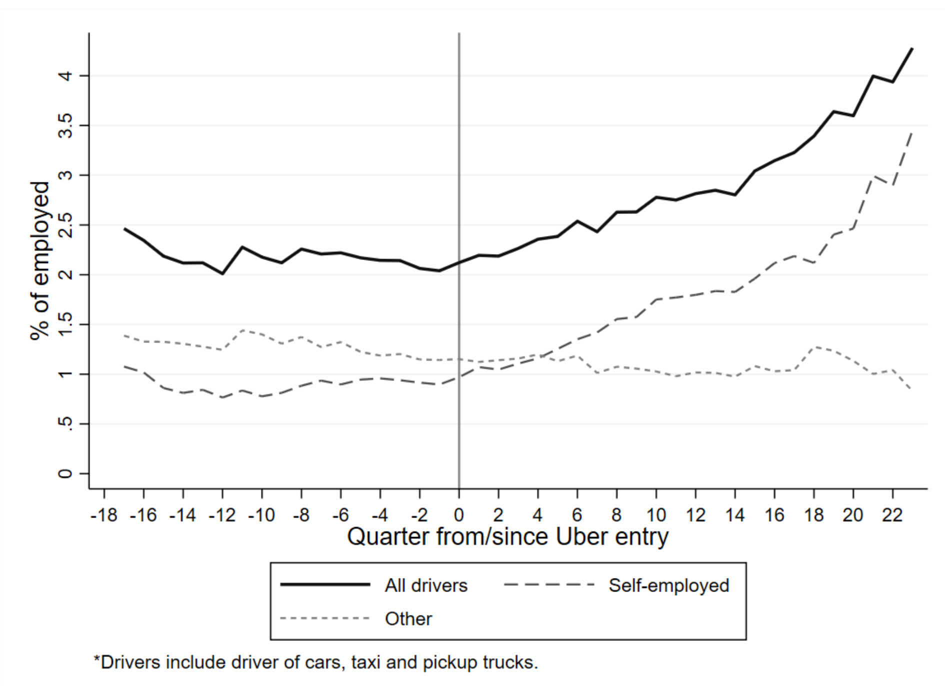


Figure 2. Drivers in Brazilian capitals after Uber entry

Admittedly, not necessarily all self-employed drivers are in the ridesharing business, but it is unlikely that any reason other than the entry of ridesharing companies would explain such a marked trend. Further, even though I cannot distinguish between ridesharing and non-ridesharing self-employed drivers, the latter is also a group of interest, also impacted by the entry of ridesharing companies. *Therefore, the self-employed driver variable captures workers who are either ridesharing drivers or have been directly impacted by the ridesharing business*.

Throughout the analysis, I compare self-employed drivers with four mutually exclusive categories: i) informal workers, ii) formal workers, iii) other (non-driver) self-employed, and iv) other drivers (not self-employed).[10] Informal and formal workers, and other self-employed serve as control groups to the extent that identified trends that are exclusive to self-employed drivers are likely caused by ridesharing. These groups also represent the largest contingents of the workforce and are unlikely to be significantly affected by the ridesharing industry. Distinctly, other drivers (not self-employed) are included as a group of interest but not a control per se, as it is likely affected by the ridesharing industry, violating difference-in-difference identification assumptions.

By relying on pooled cross-sections, one limitation of this identification strategy is the inability to distinguish to what extent the trends observed in the dependent variables derive from changes in the composition of drivers or by restrictions imposed by ridesharing companies (e.g., price definition mechanisms). Such a limitation is circumvented in two ways. First, in the robustness checks section, I rely on coarsened exact matching (Iacus, King, and Porro 2012) to study the pooled models on a sample that is constructed to resemble the pre-ridesharing period. Then, in the last section, I take advantage of PNADC's rotating component to reduce the sample

[10] The distinction between workers in formal and informal arrangements is based on whether they have a formal employment contract (Ulyssea 2020; Roubaud et al. 2020).

to a pseudo-panel of workers who were interviewed while Uber arrived in their cities. In such a subsample, individual-level fixed effects models improve inference by removing unobservable individual biases. As a limitation, individuals in the pseudo-panel can be traced for up to five consecutive semesters, restricting the results to short-term effects.

Finally, omitted variables correlated with the Uber rollout order are potential threats to the identification strategy. Although the company's decision criteria are unclear, previous studies find metropolitan area size to be an important determinant in Brazil and the United States (Berger, Chen, and Frey 2018; Barreto, Silveira Neto, and Carazza 2021), such that controlling for area fixed effects partially tackle this problem in the staggered models. Additionally, the canonical difference-in-difference models discussed in section 2.8 check the robustness of findings in a simpler before-and-after set up.

2.5.2 Econometric Models

As discussed, the data comprises a pooled cross section at the individual level from 2012 to 2019, in which city of residence was used to define pre- and post-ridesharing periods. I now turn to the regression models.

The first theoretical model study changes in the log-likelihood of workers being employed as self-employed drivers before and after Uber launched in their cities. In equation (1), $SEDriver_{i,t,j}$ is a dummy capturing whether the individual i in city j and year-quarter t is employed as a self-employed driver. The model assume that the probability takes the form of the logistic function G.[11] $Uber_{t,j}$ is a dummy that captures when Uber entered each metropolitan area,

[11] Across all logit models, the probability of an individual being a self-employed driver P is estimated as the logarithm of the odds or $\log(P) = \log\left(\frac{P}{1-P}\right) = \alpha_j + \alpha_t + \beta Uber_t + \theta X_i + \delta(Uber_t * X_i)$, using maximum likelihood.

and X_i is a vector of individual characteristics, including gender, race, marital status, education, and age. β captures changes in the log-likelihood of individuals being self-employed drivers. Finally, α_j is a vector of dummies for each metropolitan area, and α_t is a vector containing quarter dummies.

$$P(SEDriver_{i,t,j} = 1) = G(\beta Uber_{t,j} + \theta X_i + \alpha_j + \alpha_t \,) \tag{1}$$

Equation (1) is also ran with all drivers and not self-employed drivers and the dependent variable. If β is positive and significant across all three models, this study would capture the growing popularity of the driver occupation, not necessarily related to ridesharing. However, if β is positive in all specifications except for not self-employed drivers, then ridesharing is likely an underlining cause of the expansion of the driver occupation observed in Figure 2.

Equation (2) is similar to (1), except for the fact that it allows interactions between $Uber_{t,j}$ and X_i. As such, δ captures how the driver profile has changed after ridesharing entry.

$$P(SEDriver_{i,t,j} = 1) = G(\beta Uber_{t,j} + \theta X_i + \delta(Uber_{t,j} * X_i) + \alpha_j + \alpha_t) \tag{2}$$

Next, equation (3) illustrates a staggered difference-in-differences model that identifies differences in trends in job outcomes of self-employed drivers compared to other groups. The dependent variable, $y_{i,t,j}$, is either of the following job outcomes for worker i in city j and year-quarter t: logarithm of earnings, logarithm of hourly earnings, weekly hours worked, and contribution to social security (dummy). Linear models are used to estimate the continuous dependent variables and logit regressions for the dummy one. The categorical variable $TYPE_i$

distinguishes self-employed drivers (the base group) from the other four types: other driver (not self-employed), informal worker, formal worker, and other self-employed (not driver). The interaction between $Uber_{t,j}$ and this categorical variable allows capturing how Uber's entry has impacted self-employed drivers compared to other workers – the control groups. Finally, $e_{i,t,j}$ represents the error term.

$$y_{i,t,j} = \beta Uber_{t,j} + \theta X_i + \varphi TYPE_i + \delta(Uber_{t,j} * TYPE_i) + \alpha_j + \alpha_t + e_{i,t,j} \qquad (3)$$

Finally, taking advantage of the rotating panel component of PNADC, I restrict the sample to a pseudo-panel of workers who showed up at least three and up to five quarters in the data. I keep in the data individuals in Uber transition periods, corresponding to those for whom I could identify at least one quarter pre- and post-Uber entry, and who worked as a self-employed driver at least in one but not all periods. Such restrictions reduce the sample to a panel of 1,639 observations. Although significantly smaller, this panel allows me to observe job transition probabilities from various job statuses (e.g., other jobs, unemployed, and out of the labor force) to self-employed driving, net of individual unobserved heterogeneity.

The equation in (4) represents a theoretical model, in which $SEDriver_{i,t,j}$ is a dummy variable for individuals i who are self-employed drivers in period t, $Uber_{t,j}$ is a dummy variable capturing the presence of Uber in the city j and time t, and $Status_{i,t-1,j}$ represents the individual job status in the previous quarter (self-employed driver, other driver, other job, unemployed, or out of the labor force). As before, the probability is estimated using the logistic function G. Finally, α_i represents a vector of individual fixed effects.

$$P(SEDriver_{i,t,j} = 1) = G(\alpha_i + \beta Uber_{j,t} + \varphi Status_{i,t-1} + \delta(Uber_{j,t} * Status_{i,t-1})) \quad (4)$$

2.6 Descriptive Results

2.6.1 Changes in Demographic Profiles

Table 2 illustrates the share of each employment group across the years. Although self-employed drivers remain a small fraction of the employed population, their share has more than doubled between 2012 and 2019. *Indeed, within the occupational distribution, self-employed drivers moved from the 25th to the 7th most common occupation in Brazilian capitals in this period*. Table 2 also shows a labor de-regulation trend, with steadily decrease in formal jobs and an increasing presence of self-employment.[12]

Table 2. Groups of Workers by Year (Percent)

Group	2012	2013	2014	2015	2016	2017	2018	2019
SE Driver	0.90	0.84	0.91	0.98	1.23	1.47	1.84	2.30
Other Driver	1.28	1.34	1.38	1.30	1.16	1.08	1.10	1.04
Informal Worker	16.66	16.03	15.28	15.65	15.83	16.86	17.53	17.85
Formal Worker	58.10	58.55	58.94	57.51	56.06	53.83	52.25	50.90
Other SE	23.06	23.24	23.49	24.56	25.72	26.77	27.28	27.91
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
N (unweighted)	268,289	273,680	275,539	272,804	268,871	268,284	263,507	265,312

Note: Weighted tabulations from PNADC of employed workers in Brazilian capitals.

Table 3 provides evidence of demographic changes by working arrangements between 2012-2013 to 2018-2019, representing the before and after ridesharing periods. Over time, the

[12] While the literature suggests that many workers rely on ridesharing as a secondary job, this does not seem to be the case for most drivers in Brazil. Even though there was an increase in the proportion of workers who are self-employed drivers as a second job – growing to be *the third most common second job in 2019* – the multiple job holding rate in Brazil has remained stable over time at about 3 percent of the employed population (Figure A1 in Appendix A). Thus, as most self-employed drivers drive as their primary job and the multiple job holding rate is stable, this essay focuses on individuals' main jobs only.

workforce demographic profile has changed, revealing higher educational attainment levels and presence of black workers across all arrangements. Women, who still predominate in informal jobs, saw their participation increase in the formal jobs and self-employment.

Table 3. Demographic Characteristics of Drivers and Non-Drivers in Brazilian capitals

Variable	Group	2012-2013	Difference (2018-2019)
Female	SE Driver	0.08	-0.01*
	Other Driver	0.03	-0.00
	Informal Worker	0.61	-0.01***
	Formal Worker	0.44	0.02***
	Other SE	0.40	0.01***
Black	SE Driver	0.50	0.05***
	Other Driver	0.58	0.04***
	Informal Worker	0.60	0.01***
	Formal Worker	0.53	0.03***
	Other SE	0.55	0.02***
Married	SE Driver	0.73	-0.09***
	Other Driver	0.67	0.01
	Informal Worker	0.50	-0.01***
	Formal Worker	0.55	0.02***
	Other SE	0.65	-0.02***
Age	SE Driver	46.35	-2.99***
	Other Driver	40.54	2.25***
	Informal Worker	39.09	0.83***
	Formal Worker	36.73	1.59***
	Other SE	44.26	0.07
Less than High School	SE Driver	0.46	-0.18***
	Other Driver	0.49	-0.08***
	Informal Worker	0.53	-0.11***
	Formal Worker	0.34	-0.08***
	Other SE	0.54	-0.12***
College or Higher	SE Driver	0.06	0.05***
	Other Driver	0.03	0.02***
	Informal Worker	0.13	0.06***
	Formal Worker	0.19	0.07***
	Other SE	0.14	0.07***

Source: Authors' tabulations from quarterly PNADC 2012, 2013, 2018, and 2019. Difference column shows difference of means tests. *** p<0.01, ** p<0.05, * p<0.1

Across groups, self-employed drivers are somewhat distinct from all others. The driver profession (self-employed or not) remained dominated by men over the period, contrasting with the other categories, which reveal a more even gender makeup (or are predominated by females as in the case of informal workers). Self-employed drivers are also older, more likely to be married, and less educated than most groups.

Within group, in the post-ridesharing period, self-employed drivers were more likely to be men[13], black, and single than prior to ridesharing. They were also younger and more educated than before. Indeed, the increase in the presence of college degree holders was disproportionately higher for drivers, nearly doubling. In this regard, Schor (2017) argues that, if generalized, the trend of high-skill workers occupying low-skilled jobs could become a driver of inequality.

2.6.2 Changes in Job Outcomes

This section investigates changes in mean monthly earnings, weekly hours worked, and subscription to social security rates for self-employed drivers and the comparison groups. *Trends exclusive to self-employed drivers and no other group are likely caused by the entry of ridesharing firms or associated responses rather than other shocks*. Further, the visual inspection of these averages allows assessing the adequacy of the control groups regarding expectations of parallel trends prior to ridesharing.[14] Simultaneously, the graphs allow observing which groups are more similar to self-employed drivers in each job outcome over time. In Figure 3 to Figure 5, thicker lines represent the means, thinner lines the 95 percent confidence intervals, and the blue lines mark the quarter in which Uber entered the first (Rio de Janeiro – 2014Q3) and the last capital (Macapa – 2017Q3) in Brazil.

[13] However, as discussed in Chapter 3, the reduction in the proportion of female drivers over the period is driven by a higher absolute growth of male drivers. Within gender, there has been a growth in the proportion of both male and female drivers.

[14] Formal tests are available in Table A4 to Table A7 in Appendix A.

Unlike other groups, self-employed drivers experienced a substantial reduction in monthly earnings over the period, moving from the highest earners to levels similar to other groups except for formal workers (Figure 3). Although not as drastic, a reduction also occurred in the average number of hours worked. Still, self-employed drivers continue to work longer schedules than most other groups (Figure 4). A detailed distribution of usual hours worked reveals that the average decrease was mostly driven by a reduction in the proportion of drivers driving at the higher end of the hours' distribution (Figure A2 in Appendix A). However, most drivers in 2018-2019 still drove at least 40 hours a week.

Translated into hourly earnings, self-employed drivers made higher profits than other drivers and informal workers in the pre-ridesharing period but caught up with them over time. Simultaneously, while they had similar hourly earnings to formal workers and other self-employed, they were clearly in a deteriorated position in the post-ridesharing period (Figure A3 to Figure A6 in Appendix A). Importantly, these figures do not account for the operational costs, which, in ridesharing, are a worker's responsibility. The earnings reduction was followed by a decrease in subscription to social security rates, approximating self-employed drivers to other self-employed and informal workers (Figure 5). Such a reduction raises a flag for increased vulnerability, especially in light of the aging population trend and given that most drive as a full-time job.

Across the figures, the four comparison groups reveal relatively stable trends over time, and the parallel trends prior to Uber entry seem to hold upon visual inspection.

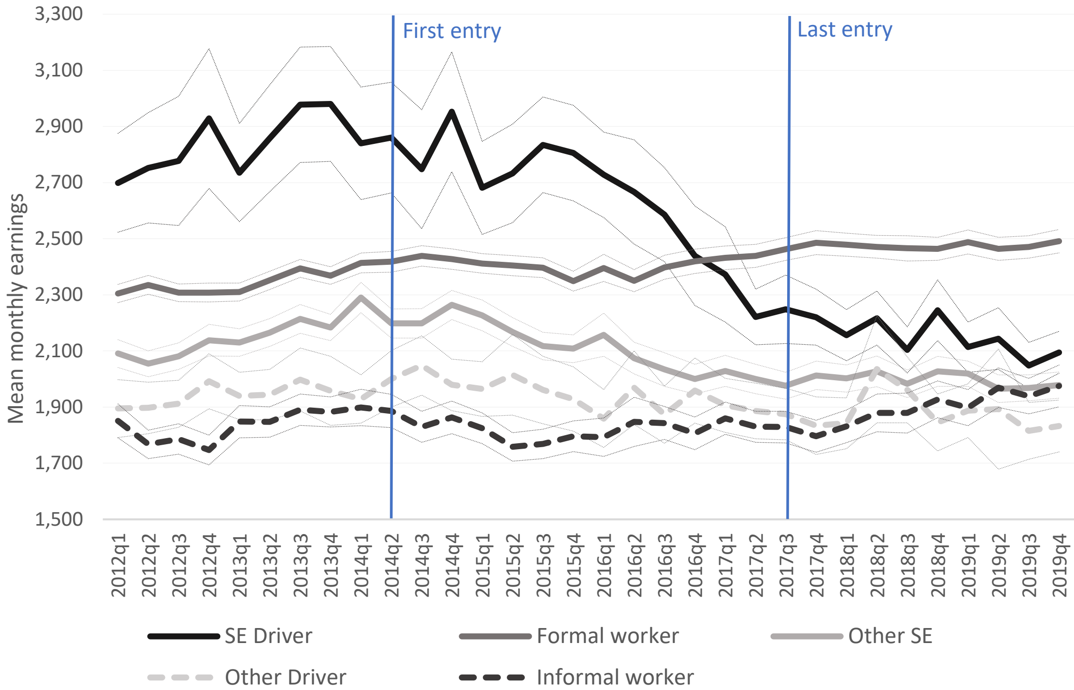


Figure 3. Mean Monthly Earnings

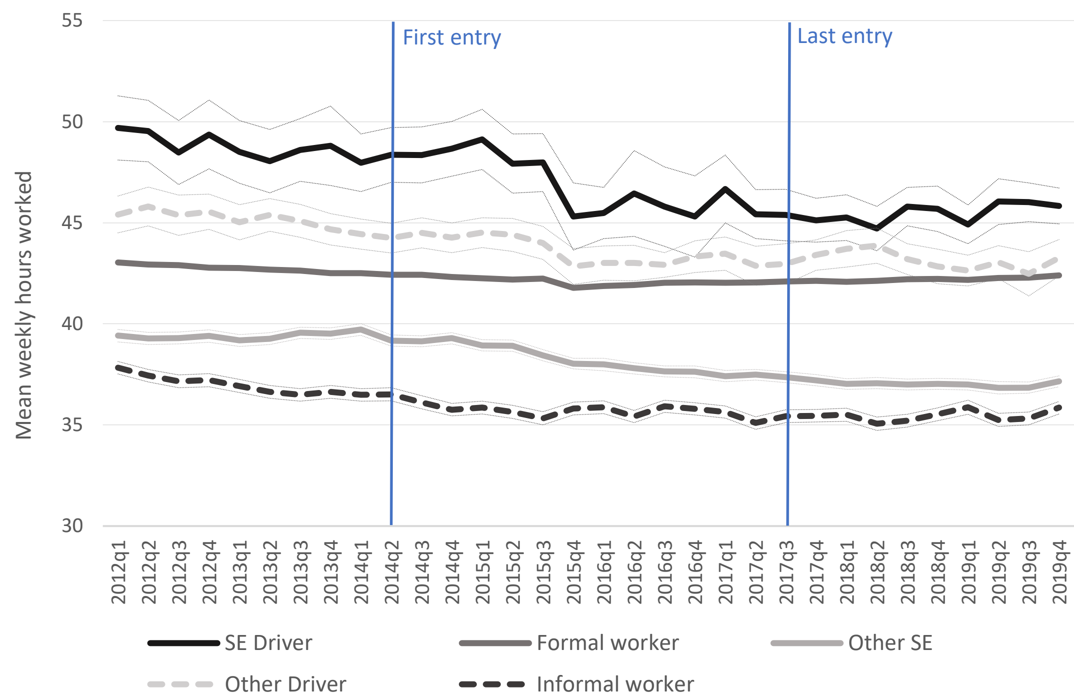
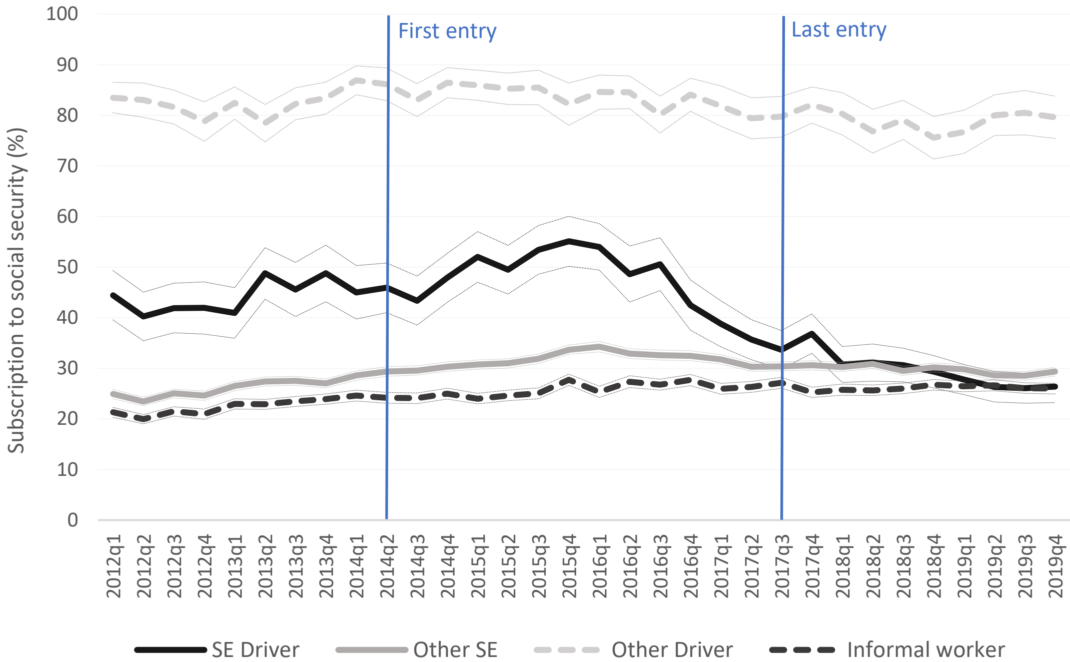


Figure 4. Mean Weekly Hours Worked



*Formal worker: 100%, by definition.

Figure 5. Mean Subscription to Social Security (INSS) Rates

2.7 Regression Results

2.7.1 Driver Demographics

I begin this section by estimating the log odds of workers being employed as drivers in the post-ridesharing period. The discussion centers on graphical representations of predicted marginal probabilities, but full regressions are available in Table A3 in Appendix A.

Figure 6 plots the results obtained from equation (1), confirming once again that individuals were more likely to be drivers in the later period and that such an increase was pushed exclusively by self-employed drivers. Specifically, workers' probabilities of being self-employed drivers grew from roughly 0.8 to 1.6 percent between the periods.

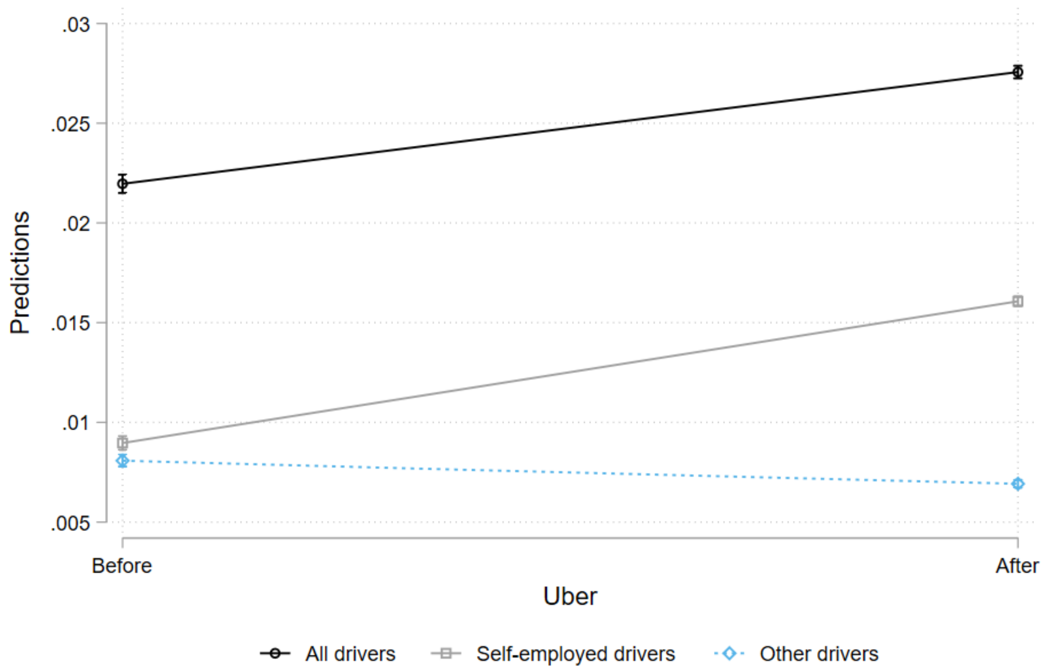


Figure 6. Probabilities of Working as a Driver before and after Ridesharing

Note: Predictive margins and confidence intervals from logistic regressions on all drivers, self-employed drivers, and not self-employed drivers. All models include demographic controls and metropolitan and quarter fixed effects. Standard errors clustered at the metropolitan level. Source: Authors' calculations from quarterly PNADC 2012-2019. Full results are shown in Table A3 in Appendix A (columns 1-3).

Not only self-employed driver became a more common occupation in the post-ridesharing period, but there were changes in the composition of this group in the workforce, as documented in section 2.6.1. Figure 7 plots predicted probabilities of being a self-employed driver before and after Uber based on the logistic regression specified in equation (2). Overall, all demographic variables were associated with higher probabilities of working as self-employed drivers in the post-ridesharing period, but the increases were particularly high for men and highly educated individuals. The increased probabilities for those with a college degree or higher are somewhat surprising but may be explained by the lower car ownership rates in Brazil.

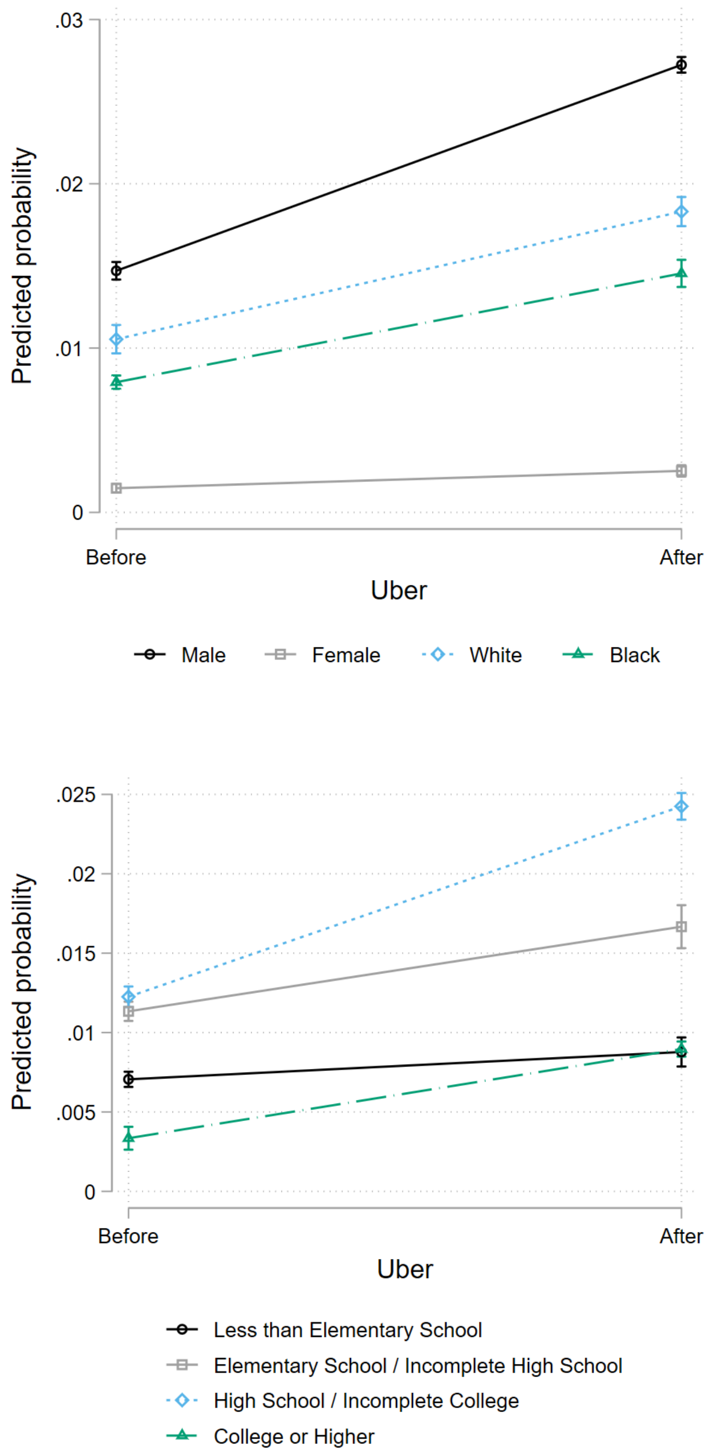


Figure 7. Predicted probabilities of Self-Employed Driving by Demographics

Note: Marginal predictions and confidence intervals based on a logistic regression with interactions between post-ridesharing and worker demographic characteristics. The model includes metropolitan and quarter fixed effects. Standard errors clustered at the metropolitan level. Full results are shown in Table A3 in Appendix A (column 4).

2.7.2 Changes in Job Outcomes: Self-Employed Drivers versus Other Workers

Table 4 illustrates models on the job outcome variables, in which the columns earnings, hourly earnings, and weekly hours worked are linear regressions, and social security contributions are logistic models. The negative coefficients on post-ridesharing across models confirm the findings from the descriptive section, namely that self-employed drivers had lower earnings – in total and hourly, worked fewer hours, and were less likely to contribute to social security in the post-ridesharing period.

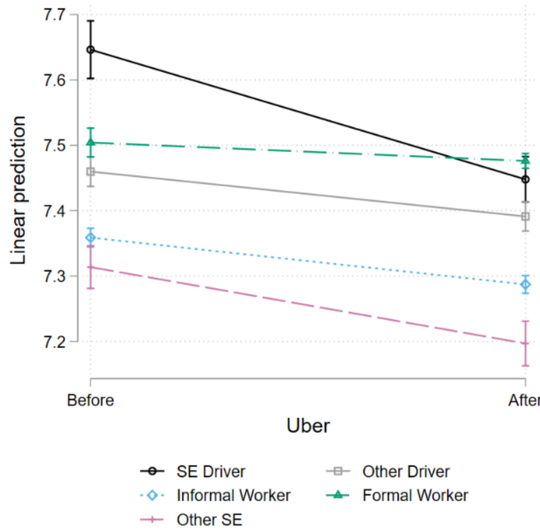
Non-interacted coefficients on the groups of workers confirm that they earned less (monthly and hourly) but worked fewer hours than self-employed drivers in the pre-ridesharing period. However, the positive interactions with post-ridesharing indicate either a reduction or a reversal of these gaps. The logit model reveals that self-employed drivers had higher log-likelihoods of contributing to social security than informal workers and other self-employed prior to ridesharing, an advantage that has disappeared in the post-Uber period. Meanwhile, the difference in contribution rates with other drivers – who already had higher subscription rates – has increased.

Figure 8 plots predicted job outcomes of all groups, estimated from marginal effects of regressions as in equation (3). The figure provides a graphical illustration of the main findings of this study, namely, that there has been an important decrease in the earnings, hours of work, and social security contributions of self-employed drivers across the decade. While these changes made self-employed drivers more similar to other groups in the Brazilian labor market, they also reveal important job quality losses within the category. In the future, it will be important to trace these changes to assess whether there will reach a stabilization point or a continue to decline.

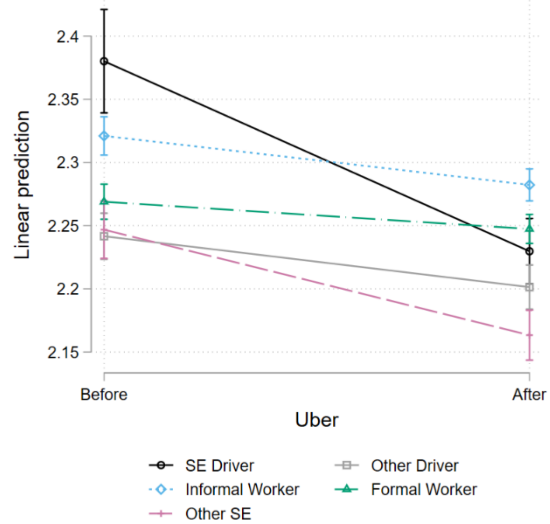
Table 4. Staggered Difference-in-Differences Specifications

Variables	Log. Monthly Earnings (1)	Log. Hourly Earnings (2)	Weekly Hours Worked (3)	Social security (logit model) (4)
Uber	-0.20***	-0.15***	-2.34***	-0.50***
	(0.02)	(0.03)	(0.66)	(0.07)
Other Driver	-0.19***	-0.14***	-3.93***	2.13***
	(0.03)	(0.03)	(0.39)	(0.13)
Informal Worker	-0.29***	-0.06**	-9.50***	-0.80***
	(0.02)	(0.02)	(0.57)	(0.11)
Formal Worker	-0.14***	-0.11***	-4.18***	
	(0.03)	(0.02)	(0.50)	
Uber * Other Driver	-0.33***	-0.13***	-7.85***	-0.77***
	(0.02)	(0.02)	(0.56)	(0.06)
Uber * Other Driver	0.13***	0.11***	1.06	0.19
	(0.02)	(0.03)	(0.73)	(0.12)
Uber * Informal Worker	0.13***	0.11***	1.25*	0.50***
	(0.01)	(0.02)	(0.69)	(0.08)
Uber * Formal Worker	0.17***	0.13***	1.94***	
	(0.02)	(0.03)	(0.66)	
Uber * Other SE	0.08***	0.07**	0.90	0.60***
	(0.02)	(0.03)	(0.64)	(0.08)
Constant	7.17***	1.80***	49.18***	-2.09***
	(0.03)	(0.02)	(0.44)	(0.14)
Observations	2,156,286	2,156,286	2,156,286	1,005,415
R-squared / Pseudo R-squared	0.41	0.39	0.10	0.12

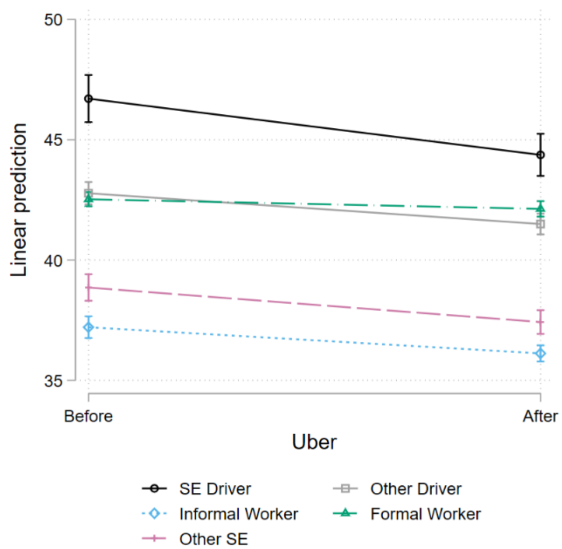
Note: All models include demographic controls, and quarter and metropolitan fixed effects. Post-ridesharing assumes the value one from the quarter in each Uber entered each metropolitan area, and zero prior to it. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1



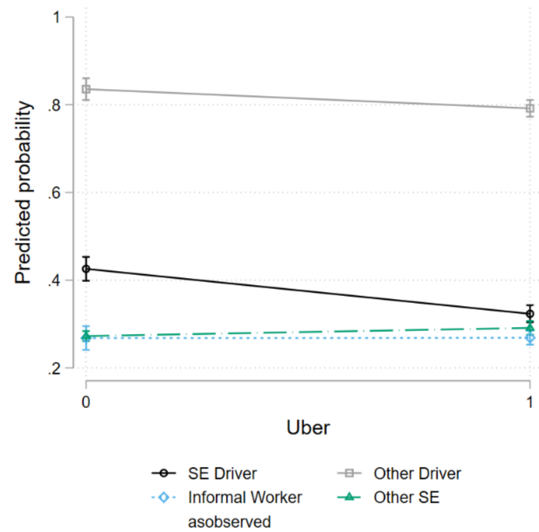
a. Log Monthly Earnings



b. Log Hourly Earnings



c. Weekly Hours Worked



d. Social Security Subscription

Figure 8. Predicted Job Outcomes

Note: Marginal predictions and confidence intervals of models shown in Table 4.

2.8 Robustness Checks

This section checks the robustness of the findings. A natural starting point in the difference-in-differences framework is to formally check if the parallel assumptions hold. The second test investigates biases caused by heterogeneous treatment effects. Finally, I study whether compositional changes in the workforce may have driven the results.

To check for parallel trends assumption in the pre-Uber period, I run the regressions contrasting self-employed drivers to the comparison groups. In (4), $y_{i,t,j}$ represents the expected job outcomes of individual i in city j and year-quarter t. $TYPE_i$ is a dummy assuming value one for self-employed drivers and zero for other job, considering each possibility at a time. yq_t is a vector of year-quarter indicators, and α_j is a vector of metropolitan fixed effects. The interaction coefficient, $\delta,$ captures if group differences remain constant over time. As before, linear regressions are used to estimate total earnings, hourly earnings, and hours of work, and a logistic regression is adopted for social security subscription.

$$y_{i,t,j} = \beta TYPE_i + \varphi YQ_t + \delta(TYPE_i * YQ_t) + \alpha_j + e_{i,t,j} \tag{4}$$

As shown in Table A4 to Table A7 in Appendix A, there are no significant differences in trends between self-employed drivers and the other groups in most periods. Exceptionally, differences in expected earnings of informal workers and self-employed drivers vary significantly over time, violating the parallel trends assumption. However, excluding informal workers from the earnings models does not alter the conclusions (Table A8 in Appendix A). The second concern regards whether the estimates are biased by heterogeneous treatment effects, a common treat to the validity of staggered difference-in-difference models (Goodman-Bacon

2021; Callaway and Sant'Anna 2021). To rule-out that concern, the sample was reduced to the years 2012, 2013, 2018, and 2019, such that a pre- and post-Uber was defined independently form the rollout period. The model in (5) is similar to the one described in (3), except that $Uber_{t,j}$ is now replaced by $POST_{t,j}$, a dummy variable equal to one for years 2018 and 2019, and equal to zero for the years 2012 and 2013. As per Table 5, not only does the canonical difference-in-differences models reinforce the conclusions, but the coefficients are even larger in magnitude. As such, heterogeneous treatment effects may have deflated the estimates but not the opposite, which would have been far more concerning.

$$y_{i,t,j} = \beta POST_{t,j} + \theta X_i + \varphi TYPE_i + \delta(POST_{t,j} * TYPE_i) + \alpha_j + \alpha_t + e_{i,t,j} \quad (5)$$

A final concern is whether the results were driven by changes in the composition of self-employed drivers. To test that, I adopted a coarsened exact matching strategy to generate a sample in the post-Uber period that mirrored that of the previous period in observable characteristics (Iacus, King, and Porro 2012). For each metropolitan area, individuals were matched on race, sex, age, marital status, and job category. The matched sample produced results remarkably similar to the ones already introduced, as shown in Table 5. As such, there is no evidence that the trends observed in job outcomes were driven by changes in the driver's profile. More likely, they are a result of ridesharing companies' policies and lack of labor regulations.

Table 5. Canonical and Staggered Difference-in-Differences on Matched Sample

Variables	Canonical DiD				Stagged DiD (Matched Sample)			
	Log. Monthly Earnings	Log. Hourly Earnings	Weekly Hours Worked	Social security (logit model)	Log. Monthly Earnings	Log. Hourly Earnings	Weekly Hours Worked	Social security (logit model)
Uber	-0.29***	-0.22***	-3.22***	-0.86***	-0.17***	-0.12***	-2.70***	-0.42***
	(0.02)	(0.03)	(1.01)	(0.10)	(0.02)	(0.02)	(0.45)	(0.05)
Other Driver	-0.20***	-0.16***	-4.01***	2.01***	-0.19***	-0.14***	-3.83***	2.17***
	(0.03)	(0.03)	(0.61)	(0.14)	(0.02)	(0.02)	(0.40)	(0.10)
Informal Worker	-0.31***	-0.08***	-9.71***	-0.86***	-0.27***	-0.05**	-9.33***	-0.65***
	(0.02)	(0.03)	(0.83)	(0.11)	(0.02)	(0.02)	(0.50)	(0.10)
Formal Worker	-0.16***	-0.12***	-4.68***		-0.13***	-0.11***	-3.94***	
	(0.03)	(0.02)	(0.73)		(0.02)	(0.02)	(0.52)	
Uber * Other SE	-0.35***	-0.14***	-8.13***	-0.81***	-0.32***	-0.13***	-7.81***	-0.82***
	(0.02)	(0.03)	(0.81)	(0.08)	(0.02)	(0.02)	(0.45)	(0.05)
Uber * Other Driver	0.20***	0.18***	1.15	0.53***	0.13***	0.10***	1.46***	0.17**
	(0.03)	(0.04)	(1.01)	(0.14)	(0.02)	(0.02)	(0.42)	(0.08)
Uber * Informal Worker	0.20***	0.18***	1.75*	0.94***	0.10***	0.08***	1.67***	0.33***
	(0.02)	(0.03)	(1.00)	(0.10)	(0.01)	(0.01)	(0.45)	(0.06)
Uber * Formal Worker	0.26***	0.20***	2.93***		0.15***	0.10***	2.36***	
	(0.02)	(0.03)	(0.98)		(0.01)	(0.02)	(0.41)	
Uber * Other SE	0.12***	0.11***	1.05	0.91***	0.05***	0.03**	1.26***	0.52***
	(0.02)	(0.03)	(0.95)	(0.07)	(0.01)	(0.01)	(0.39)	(0.05)
Constant	7.18***	1.80***	50.37***	-2.14***	7.16***	1.80***	48.98***	-2.15***
	(0.03)	(0.02)	(0.65)	(0.15)	(0.03)	(0.02)	(0.46)	(0.11)
Observations	1,070,788	1,070,788	1,070,788	507,264	4,270,692	4,270,692	4,270,692	1,986,501
R-squared / Pseudo R-squared	0.41	0.38	0.11	0.118	0.39	0.37	0.10	0.124

Note: In the canonical difference-in-differences specifications, post-ridesharing is equal to one for 2018-2019 and zero for 2012-2013. In the matched models, the sample was re-weighted and restricted to look similar to that prior to Uber entry in observable characteristics: race, sex, age, marital status, job type, and metropolitan area. All models include demographic controls, and quarter and metropolitan fixed effects. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

2.9 Job Transitions: Panel Subsample

This section restricts the analysis to a pseudo-panel, a subset of workers for whom information was available between three and five consecutive quarters and whose interviews coincided with a period in which Uber entered their cities. The panel allows the direct observation of changes in the probabilities of transition between job status before and after Uber, net of individual unobserved heterogeneity.

As shown in Figure 9, there has been an increase in the probability of transitioning to self-employed driving from informal, self-employed, other driver, and unemployed. The case of unemployment is especially marked, with transitioning probabilities growing from roughly 30 to 75 percent before and after Uber, respectively. Self-employed driving has also attracted those who were driving as employees. In the meantime, it does not seem that, in the short-run, Uber was as an attractive alternative for those who were not in the labor force. Finally, the probability of remaining a self-employed driver has reduced in the post-Uber period, suggesting that this activity is a short-term option.

As far as job outcomes, the models portrayed in Table A9 in Appendix A reveal lower earnings, in total and hourly, and lower likelihoods of subscribing to social security following Uber entry, hence, confirming prior conclusions. However, the model finds no significant difference in the number of hours of work, which may reflect stickiness of individual behavior regarding work schedule in the short run.

An un unfortunate limitation of this set-up is its inability to capture the long-term impacts of Uber entry. Again, such a limitation is imposed by the survey design, as the panel does not extend longer than five consecutive quarters. However, even in this short period, the analysis reveals changes and corroborates prior literature that states ridesharing is an important alternative out of unemployment.

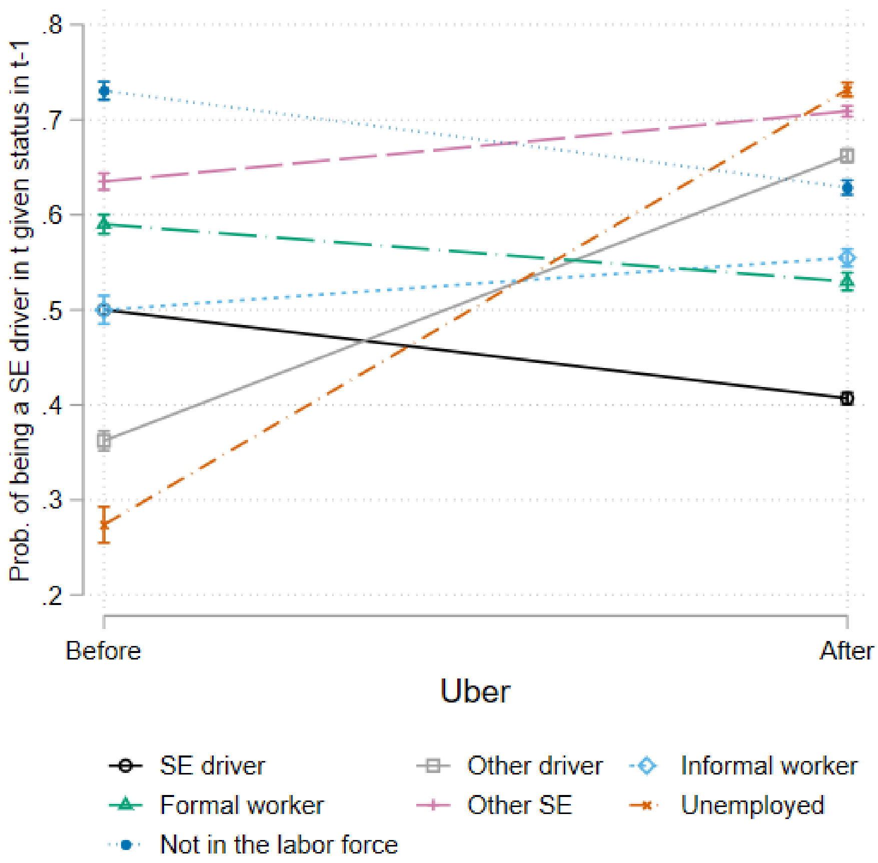


Figure 9. Predicted Probabilities of Transitioning from each Job Status (t-1) into SE Driver (t)

Note: Predictive margins with 95% confidence intervals. Logistic model as specified in equation (3). N=1,639 observations in 444 groups. Full regressions show in Table A9 in Appendix A.

2.10 Conclusion

Since its launching, ridesharing has quickly spread to thousands of cities worldwide, offering consumers a new travel alternative and providing a flexible job opportunity with low-entry barriers to workers. Further, the ridesharing model has expanded to other sectors, including services such as delivery and shopping, suggesting the success of this business model. From the start, however, ridesharing has been followed by discussions regarding worker classification, as their lack of recognition as employees has implications for labor protections. In response to these discussions, research has investigated questions such as who engages in platform work, their reasons, and job outcomes. However, as the literature review suggests, these findings provide mixed pictures. For example, while the first studies found that platforms mostly supplement income, more recent studies identify ridesharing as increasingly replacing traditional employment. Likewise, the evidence on earnings is mixed and varies over time.

The present study contributes to advancing the literature on ridesharing in two ways. First, by focusing on Brazil, it illustrates the implications of the model in a middle-income country context. Not only do these countries represent important shares of the ridesharing market – with Brazil being the second largest Uber market globally – but their labor markets are typically distinct from high-income countries due to the higher concentration of informality, for example. Second, by covering the impacts of ridesharing over a more extended period (2012-2019), it conciliates some findings from the literature on the short- and long-run impacts of ridesharing.

Using Uber entry as a proxy for ridesharing, this study shows a spike in the number of self-employed drivers, growing to be the 7th most common occupation in 2019. Although not every self-employed driver is necessarily a ridesharing driver, it seems unlikely that such a spike would have been caused by factors unrelated to the ridesharing entry. Further, while there are similar increases in the number of secondary-job self-employed drivers, the majority of workers drive as a primary job, typically with longer schedules than comparable workers in other arrangements.

To understand the driver profile and the implications of ridesharing in context, I create four comparison groups (informal workers, formal workers, other self-employed workers, and other drivers). In this setting, any observed trends that are exclusive of self-employed drivers and no other group are interpreted as being caused by ridesharing.

While ridesharing drivers remain somewhat different from all comparison groups, the study highlights changes in their demographic profile in the post-ridesharing period, of which the increasing presence of highly educated workers is perhaps the most striking. Why are highly educated workers becoming self-employed drivers? Are they attracted to the job flexibility? Are opportunities lacking in their area of specialization? Although the unequal access to car ownership in Brazil may explain this result, a better assessment will require further research.

Regarding job outcomes, as the number of drivers grew, the total earnings gradually reduced such that, in the post-ridesharing period, self-employed drivers made fewer earnings in total and hourly. Although still working more hours than other groups on average, there has also been a decrease in weekly work hours. Finally, self-employed drivers' probability of subscribing to social security has markedly declined while remaining relatively stable to other workers. Taken together, at the end of the period, self-employed drivers increasingly resembled other workers in the economy.

The negative trends in social security contributions – added up to the fact that ridesharing is mainly a primary job – are concerning and capture an increasing informal or unprotected workforce. Indeed, in the Brazilian context, self-employed drivers are informal by default, but they can independently seek formalization by registering as self-employed workers or micro-entrepreneurs. In both cases, contribution to social security would capture these formalization decisions. However, results clearly show that formalization has not been a priority.

There is no evidence that the highlighted findings were driven by changes in the demographic composition of workers. Alternatively, they are plausibly driven by market responses to the shift in the labor supply of drivers, currently larger than ever before. In this regard, a crucial question moving forward is whether the earnings and hours declining trends will stabilize or continue, and whether the new market equilibrium will be considered acceptable from a normative standpoint. Indeed, regulatory responses can play a crucial role in establishing minimum labor standards when the market fails to do so, particularly in cases where monopolistic tendencies emerge.

A question that remains unanswered is whether self-employed driving is a short- or long-run activity. If workers are self-employed as a transition phase, vulnerability might be temporary. If self-employed driving is a longer-term activity, the problem is more severe. My short-term analysis using PNADC rotating panel suggests ridesharing as an alternative to unemployment, but not necessarily a choice that extends over a longer period. In the post-ridesharing period, there has been a decline in the self-employed retention across quarters. However, given the limited panel length (3-5 quarters), these findings cannot be extended over the long run.

Regardless of how long people remain self-employed drivers, workers should be entitled to labor protections, especially since this is now one of Brazil's most common full-time jobs. While a definitive solution to the vulnerability problem requires moving past the worker classification debate, incentives for formalization in the short run could mitigate it. Indeed, in the Brazilian context, instruments are in place to reduce the costs and simplify the formalization of self-employed workers. For example, regulations could force or nudge ridesharing companies to require full time drivers to contribute to social security as individual microentrepreneurs, perhaps sharing part of the cost.

Overall, the lesson from this study calls for policymakers' attention in Brazil and elsewhere. Ridesharing has simultaneously generated a job opportunity for millions of workers and added up to the – already large – contingents of unprotected labor. As such, while the model is unique in connecting workers and jobs, it is also not so different from other forms of deregulated labor. Therefore, absent regulations that require otherwise, ridesharing will continue to gain contours of informality and expand the insecurity frontier to new groups of workers.

Chapter 3: The Impacts of Ridesharing in Brazil: A Gender Analysis

3.1 Introduction

Although female labor force participation and education levels have disproportionately increased in the past decades, there are still persistent gender differences in the labor market. Women typically have lower labor force participation rates, work fewer hours, and receive fewer earnings than men, despite having higher educational attainment levels. At least part of these differences stem from the fact that women are typically in charge of most of the unpaid household labor, including childbearing. Indeed, even among graduates from elite schools, men and women start their careers at similar points, but the pay gap shows up over time, especially after the first child is born (Bertrand, Goldin, and Katz 2010). Consequently, women are more likely to self-select into flexible arrangements than men, as flexibility allows a better balance between work and family responsibilities.

While there have always been working arrangements offering different types of flexibility, ridesharing takes it to a level not yet seen while imposing low entry barriers (owning or borrowing a car and passing a background check). In ridesharing, individuals decide whether and how much to work and may adjust their schedule instantly, making it easier to combine multiple jobs and family responsibilities, and adjust the work routine to external shocks. Other employment arrangements hardly – if ever – allow degrees of flexibility as high as ridesharing, particularly in low-wage sectors (M. K. Chen et al. 2019).

In theory, ridesharing seems like an ideal alternative for women with constraints to join the labor force or who are willing to switch to a more flexible job. If that is the case, there should be an increase in the number of female drivers following the arrival of ridesharing, especially of women with higher constraints, such as mothers. Simultaneously, the driver occupation has been historically dominated by men, partly due to cultural barriers and safety concerns. If these barriers cannot be overcome, ridesharing is less of an opportunity for women than it is for men. Whether and how women overcame the cultural barriers to take advantage of the ridesharing flexibility, and to which extent their response differed from men's, requires an empirical investigation. Indeed, as most drivers are men, an analysis that fails to differentiate groups is likely biased by them. Importantly, gendered impacts of ridesharing are likely to vary across countries, given the differences in social norms and the degree of gender equality in place.

This essay extends the previous chapter to explore gender dynamics behind ridesharing in Brazil, which is both an important market for Uber and a potentially representative case study for other middle-income countries, especially in the Latin America region. The background and research design remain similar to Chapter 2's, but the questions of interest are distinct. First, this chapter examines what characteristics make men and women more likely to drive, with attention to the gendered effects of household composition and city violence. Next, it focuses on how ridesharing has impacted the job outcomes of male and female drivers. Finally, it studies spillover effects of ridesharing in the economy by examining changes in labor force participation by gender. In doing so, it contributes to the literature on platform economy and on female labor force, as well as to the ongoing policy debate on the future of work.

Results show that, by the end of 2019, there were about 725 thousand self-employed drivers in Brazilian capitals[15], of which 6.7 percent were women. While men remain a majority, the number of female drivers grew substantially. Furthermore, determinants to become a driver and job outcomes gained from driving differ by sex. Women without children or with older children in the household (ages 7 to 15) are more likely to embrace the driver possibility in the

[15] This figure considers primary jobs, exclusively.

post-Uber period, but not those with younger children. Meanwhile, household composition has little or no effect on men's decision. Female drivers seem to take safety into account differently than male and are far less likely to work as drivers as female homicide rates increase in their cities. Earnings and work hours were more similar across sexes in the post-ridesharing period, but men experienced much higher reductions in expected earnings than women over time. Capturing ridesharing spillover effects, the paper shows that women were more likely to be in the labor force post-ridesharing, with a coefficient that is twice the size of men's.

Together, these results provide nuances on how men and women took advantage of the ridesharing possibility. However, they are not, nor intend to be, interpreted in a causal fashion. Indeed, unlike in Chapter 2, the analysis outlined herein does not include proper control groups or a strict concern over identification assumptions. Instead, it focuses on describing within and between sex differences to inform the ongoing policy debate. As a key finding, women mostly took the opportunity as expected from theory, but there are structural barriers preventing them from doing it more, including urban violence.

This essay is organized into six sections following this introduction. Section 3.2 discusses gendered differences in how men and women sort into occupations broadly and in the ridesharing-specific context. Sections 3.3 and 3.4 introduce the data and empirical strategy, and section 3.5 provides descriptive results. Section 3.6 breaks down the inferential analysis into four subsections: the probability of being a self-employed driver, effects of urban violence, changes in job outcomes, and spillover effects in labor force participation. Finally, the last section discusses the implications of these findings, limitations, and next steps.

3.2 Literature Review

Workers value job amenities differently, and such a valuation plays a role in which jobs they end up choosing. Flexibility has been an amenity much discussed in the literature, and the reasons why workers may prefer flexibility are frequently gendered biased. For instance, the literature on self-employment traditionally suggests that men's decision to become self-employed is mostly career-driven when, for women, particularly those with children, it is a decision to trade-off income in search for more flexible arrangements (Buttler and Sierminska 2020). Women are more likely than men to search for self-employment for non-pecuniary reasons, and they more often cite schedule flexibility and other family-oriented issues as reasons for becoming self-employed (Boden 1999; Sakai and Miyazato 2014).

Flexibility may appear in different forms. For example, schedule flexibility gives the worker greater autonomy and control to decide when (temporal flexibility) and where (spatial flexibility) to work. Besides facilitating work-family balance, especially for mothers, schedule flexibility may translate into higher productivity by reducing fatigue and distraction (Fuller and Hirsh 2019).

Mas and Pallais (2017) conducted a field experiment to study preferences for different types of flexibility on the call center industry and found that women are more likely than men to select flexible work arrangements, echoing the literature. However, they also found that women, especially those with young children, value working from home and avoiding irregular schedules more than schedule flexibility per se. If the stronger preference for working from home is generalizable, ridesharing might seem less appealing to mothers of young children. Instead, if women have a stronger preference for making their own schedules, ridesharing becomes an attractive option. In both cases, the household composition becomes crucial in shaping women's labor choices.

Given women's constraints, the flexible opportunity presented by ridesharing has the potential to disproportionately benefit women, allowing labor supply increases in the extensive and intensive margins. Although the literature in ridesharing and gender is still incipient, studies already indicate some gender differences. Female drivers typically drive fewer hours than men, and their hours of work are frequently shaped by household obligations and (in some countries) curfews imposed by husbands (Rizk, Salem, and Weheba 2018; Kooti et al. 2017; IFC, Accenture, and Uber 2018). In addition to flexibility, women are attracted to ridesharing to gain more independence and achieve other goals. For example, women often drive to generate extra money to support their entrepreneurial activities (IFC, Accenture, and Uber 2018). Furthermore, because women frequently come from lower-paid occupations, they experienced a higher income boost than men across six countries (Egypt, India, Indonesia, Mexico, South Africa, and the United Kingdom), ranging from 11 percent in Mexico to 29 percent in Egypt.

In practice, although there has been an overall increase in female drivers, the occupation remains dominated by men. Across the globe, female participation in ridesharing varies, with estimates ranging from 14 to 24 percent in the United States, 15 percent in Australia, about 10 percent in Malaysia, Singapore, and Canada, 5 percent in Mexico, 1 to 4 percent in the United Kingdom, 4 percent in South Africa, 1.5 percent in Indonesia and 0.2 percent in Egypt (Hall and Krueger 2018; Kooti et al. 2017; Holtum et al. 2022; Eisenmeier 2018; IFC, Accenture, and Uber 2018). In Brazilian capitals, as discussed in this paper, the number of female drivers doubled between 2012 and 2019, reaching 6.7 percent of all drivers by the end of the period (Table B1 in Appendix B).

Factors such as cultural barriers, safety concerns, and gender differences in digital inclusion help explain why the participation of women in ridesharing has remained low. Cultural barriers vary across places. For example, a survey of male drivers in Egypt and Indonesia found that more than half of them would be unhappy if a woman in their family wanted to sign up for Uber, while in India, Mexico, and the United Kingdom, more than half would be happy if they did (IFC, Accenture, and Uber 2018). Stigma, interestingly, is often expressed by family members as a fear for the women's safety (Rizk, Salem, and Weheba 2018).

However, beyond stigma, safety concerns are indeed an important barrier, highlighted by most studies identified by this literature review. Ridesharing is generally perceived by female drivers as safer than taxis, but not enough to eliminate concerns (Fileborn, Cama, and Young 2022; Rizk, Salem, and Weheba 2018; IFC, Accenture, and Uber 2018; James Holtum et al. 2022). Safety concerns translate into different uses of ridesharing, in which women are less likely to drive in more profitable times and places than their male counterparts (Holtum et al. 2022; Cook et al. 2021). In the United States, these behavioral differences have prevented the "gender-blinded" ridesharing algorithm to close the gender pay gap (Cook et al. 2021).

Importantly, these gendered perceptions of safety affect not only female drivers but also riders. Indeed, as a response, women-only ridesharing applications were launched in the United States, and now face legal prosecution for discrimination by sex. However, the model proponents argue that reading anti-discrimination laws more lightly to allow single-sex apps to run would promote public safety and social well-being (Medina 2017; Brown 2017).

Finally, digital and financial inclusion and asset ownership are other factors that limit female participation in ridesharing. Women are less likely to have bank accounts and mobile phones with internet access and to own cars (IFC, Accenture, and Uber 2018). These differences reduce the potential for women to benefit effectively from the ridesharing model.

Given the various factors that incentive and prevent women from becoming drivers, understanding who and how women engage in ridesharing, as well as their job outcomes, is an empirical question of interest from a policy and social justice perspective. As discussed, women have the potential to disproportionately benefit from ridesharing because they typically face higher constraints to participate in the labor force, which translate into higher preferences for flexibility. Importantly, the potential benefits do not nullify the concerns regarding the insecurity and precariousness associated with the gig economy discussed in Chapter 2. Instead, it adds another reason to enact regulations to make these arrangements better for workers.

This essay contributes to the literature by studying the impacts of ridesharing in Brazil from a gender perspective. As previously discussed, Brazil is the second largest labor market for Uber in the world, where ridesharing has become one of the most common occupations. And, while there has been an exponential increase in the number of women working as self-employed drivers, they remain a small proportion of drivers such that the previous findings are likely biased by men. The present chapter, then, follows as a natural step in understanding ridesharing in the Brazilian context with a gender lens. In doing so, elements known to affect men and women differently, such as household composition and safety concerns, are brought to the table.

3.3 Data

As in Chapter 2, quarterly data from the Brazilian Continuous National Household Sample Survey (PNADC) 2012-2019 comprises the main data source. The sample includes individuals aged 21 to 75 (the minimum age to work as an Uber driver and the mandatory retirement age for public and private employees in Brazil), living in capitals or the Federal District and their metropolitan areas.

In addition to the standard independent demographic variables already introduced (sex, race, age, marital status, and educational attainment level), two additional dummy variables are now included in the analysis to account for the presence of children ages 0 to 6, and 7 to 15 in the household. The threshold at 6 years old marks the beginning of mandatory education (elementary school) and an age in which children begin to gain more autonomy, and 15 is the last age before the threshold for legally working in Brazil (aka 16). These variables allow testing whether motherhood generates a different response to ridesharing. Based on the literature, by being the ones with the highest constraints, mothers would be the group more likely to benefit from the ridesharing flexibility. The presence of children in the household allows observing differences in responses between mothers and fathers.

In acknowledging safety concerns as an important factor limiting the decision to become a driver, two new variables were included in the models: transportation fatalities rates and female homicides rates, compiled by the Institute for Applied Economic Research (2023). These variables are calculated yearly at the city level and normalized by one hundred thousand population[16]. To avoid reverse causality concerns, they are included in the models with one-year lag. Including these variables allows testing whether there are gender differences in how violence affects the decision to become a driver. Summary statistics of violence variables per city are available in Table B2 in Appendix B.

[16] These variables are not available at the metropolitan level. As such, I consider the rates for the capital as proxies for homicides and transportation fatalities in their entire metropolitan areas.

3.4 Empirical Strategy

The empirical strategy includes four main parts. The first set of analysis studies the probabilities of individuals being employed as self-employed drivers – the proxy for ridesharing drivers. The second investigates the effects of violence at the city level on that probability. The third step analyzes how Uber entry has affected earnings and hours of work of self-employed drivers by gender. The last part investigates the spillover effects of Uber entry on labor force participation rates overall. Throughout the analysis, the Uber rollout is used to measure the impacts of ridesharing in Brazil as in Chapter 2. Uber is the pioneer company in most cities and the company with the highest market share to this date. However, in understanding Uber entry as a proxy for ridesharing entry more broadly, the interpretation acknowledges that changes observed are a response to a change in an industry rather than caused by a single player.

Equation (1) illustrates the first set of models, where $SEDriver_{i,t,j}$ is a dummy capturing whether the individual i in city j and year-quarter t is employed as a self-employed driver. The model assumes that the probability takes the form of the logistic function G.[17] $Uber_{t,j}$ is a dummy that captures when Uber entered each metropolitan area, and X_i is a vector of individual and household characteristics, including worker gender, race, marital status, education, age, and the presence of children in the household. Household composition variables include dummies to capture the presence of children ages 0 to 6, 7 to 15, and both. β captures changes in the log-likelihood of individuals being self-employed drivers before and after ridesharing. Lastly, α_j is a vector of dummies for each metropolitan area, and α_t is a vector containing quarter dummies.

[17] Across all logit models, the probability of an individual being a self-employed driver P is estimated as the logarithm of the odds or $logP = \log\left(\frac{P}{1-P}\right) = \alpha_j + \alpha_t + \beta Uber_t + \theta X_i + \delta(Uber_t * X_i)$, using maximum likelihood.

$$P(SEDriver_{i,t,j} = 1) = G(\beta Uber_{t,j} + \theta X_i + \alpha_j + \alpha_t) \quad (1)$$

In section 3.6.1, equation (1) is extended to include a full set of interactions between $Uber_{t,j}$ and X_i. At that point, the regressions are run separately for men and women to emphasize variations in within sex determinants to become a self-employed driver.

In section 3.6.2, city-level violence variables were included in the regressions to observe differences in responses by sex, as in (2). $V_{T-1,j}$ is a vector including fatalities in transportation rates and female homicide rates per one hundred thousand population at each city in the prior year (T-1). These models were also run separately for men and women to emphasize within sex differences, and interactions between $Uber_{t,j}$ and $V_{T-1,j}$ were included to uncover patterns of change before and after ridesharing.

$$P(SEDriver_{i,t,j} = 1) = G(\beta Uber_{t,j} + \sigma V_{T-1,j} + \theta X_i + \alpha_j + \alpha_t) \quad (2)$$

In the third step, I restrict the sample to self-employed drivers to study changes in job outcomes before and after ridesharing. Equation (3) is a linear model in which $y_{i,t,j}$ is either of the following expected job outcomes for worker i in city j and year-quarter t: logarithm of earnings, logarithm of hourly earnings, and weekly hours worked. β captures the expected change in job outcomes for men before and after Uber. φ captures the expected differences between job outcomes of men and women before Uber, and δ is the gender difference in the post-Uber period relative to pre-Uber. As in (1), X_i includes demographic and household variables, α_j and α_t are, respectively, vectors containing metropolitan and quarter identifiers, and $e_{i,t,j}$ is the error term.

$$y_{i,t,j} = \beta Uber_{t,j} + \varphi Female_i + \delta(Uber_{t,j} * Female_i) + \theta X_i + \alpha_j + \alpha_t + e_{i,t,j} \quad (3)$$

The last model studies whether ridesharing has led to spillover effects in terms of labor force participation rates. Equation (4) is a logit regression similar to (1) in which the dependent variable, $LF_{i,t,j}$, captures whether the individual is in or out of the labor force. The model is run separately for men and women and includes interactions between $Uber_{t,j}$ and all demographic characteristics, as in the extended equation (1).

$$P(LF_{i,t,j} = 1) = G(\beta Uber_{t,j} + \theta X_i + \partial(Uber_{t,j} * X_i) + \alpha_j + \alpha_t) \quad (4)$$

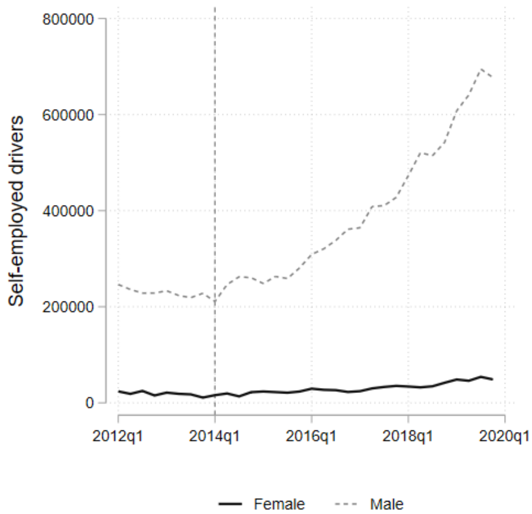
It should be noted that the goal across these models is to uncover if and how patterns differed across gender. As such, while the empirical models resemble Chapter 2, the crucial questions here are on the descriptive rather than the causal realm. Indeed, unlike before, this chapter does not include a control group per se, but instead focuses on between and within group differences.

However, by relying on a similar empirical strategy, the general concerns discussed in Chapter 2 apply here as well. To address these, tests similar to the ones discussed before are available in Table B6 to Table B8 in Appendix B. Table B6 assess whether gender job outcomes differences are parallel prior to Uber. The results show parallel trends in the log-likelihoods of working as self-employed drivers and being on the labor force, as well as in self-employed drivers' hourly earnings and weekly hours worked. Distinctly, there is evidence that the gender gap in monthly earnings was closing before Uber entry. However, unlike the trends identified in section 3.6.3, the pre-trends were driven by increases in the female driver earnings rather than decreases in male earnings. As such, it is not the case that pre-trends continued after Uber entry but instead, the patterns were reversed. Finally, as shown in Table B7 and Table B8, there is no evidence that the results are driven by heterogeneous treatment effects as canonical difference-in-differences lead to essentially the same conclusions.

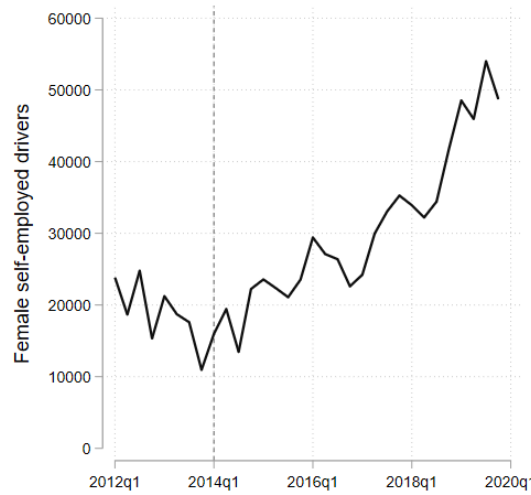
3.5 Descriptive Results

Figure 10 illustrates self-employed drivers by sex from 2012 to 2019 in Brazilian capitals. There has been a continued growth in the number of drivers since the second quarter of 2014, when the ridesharing model arrived in the country. Throughout the period, the occupation has remained dominated by men, although it grew in popularity among both sexes. By the end of 2019, there were 725 thousand self-employed drivers in Brazil, of which 6.7 percent were female. However, combining both sexes in a single chart (panel a) hides the extraordinary growth of this job among women (panel b). Indeed, the number of drivers has increased 2-fold for women and 2.7-fold for men from 2012q1 to 2019q4.

Within groups, the demographic profile of drivers also differs. Table 6 provides summary statistics for selected demographic characteristics and job outcomes of self-employed drivers two years before and two years after the Uber rollout. In both periods, self-employed men were more likely to be black, married, and were less educated than women. Post-ridesharing, fathers were more likely to drive than mothers, especially those with young children in the household – a difference that was not significant in the pre-period.



a. Men and Women



b. Women

Figure 10. Self-employed Drivers by Sex in Brazilian Capitals

Note: Table B1 in Appendix B provides the estimated number of drivers by sex in each year-quarter.

Table 6 also illustrates differences in job outcomes. On average, male self-employed drivers had higher monthly earnings than their female counterparts in 2012-2013, but the difference disappeared in the 2018-2019, not due to an increase in female earnings but rather by a decrease in male's. Men also saw a reduction in hourly earnings, dropping below women's values. Over the period, there has also been a reduction in the gender weekly hours of work gap driven by an increase in women's schedule and a decrease in men's. Overall, Table 6 suggests sex differences at both the extensive and intensive margins.

Table 6. Demographic Characteristics and Job Outcomes of Self-Employed Drivers

Variables	Pre (2012-2013) Female	Male (diff.)	Post (2018-2019) Female	Male (diff.)	Difference Post - Pre
Black (%)	41.80	9.01***	50.52	5.28***	-3.72
Married (%)	62.50	11.58***	49.59	15.47***	3.88
Elementary school (%)	32.11	15.19***	11.37	17.53***	2.34
High School (%)	56.90	-10.19***	69.18	-9.70***	1.12
College or higher (%)	10.99	-5.10***	19.45	-8.46***	-3.46*
Children ages 0 to 6 in the household (%)	13.80	2.15	8.57	8.07***	5.93**
Children ages 7 to 15 in the household (%)	26.85	-1.47	21.19	1.77***	3.24
Age (mean)	46.05	0.33	42.64	0.78	0.45
Log. monthly earnings	7.40	0.35***	7.47	0.04*	-0.31***
Log. hourly earnings	2.37	0.04	2.37	-0.13***	-0.17***
Weekly hours worked	37.68	12.14***	38.86	7.19***	-4.95***

Source: Authors' tabulations from quarterly PNADC 2012, 2013, 2018, and 2019. Difference column shows difference of means tests. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.6 Regression Results

3.6.1 Probability of Being a Self-Employed Driver

This section investigates how demographic characteristics interacted with the probability of becoming a self-employed driver before and after Uber. The models, estimated as logistic regressions specified in (1), are available in Table B3 Appendix B. However, given the various interactions included in the models, the discussion centers on graphical representations of predicted marginal probabilities.

In line with the descriptive section, Figure 11 shows an increase in the probability of being self-employed driver for both sexes before and after Uber – disproportionately higher for men. There was an increase from 1.5 to 2.7 percent in the probability of being a self-employed driver for men holding the other variables in the model constant, and from 0.15 to 0.25 percent for women.

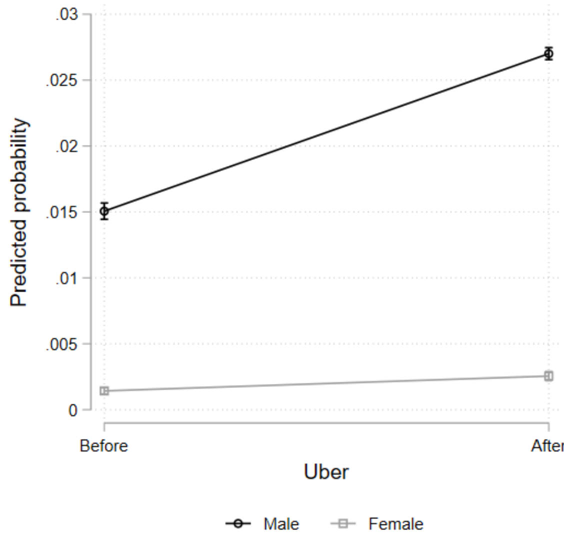


Figure 11. Predicted Probabilities of being a Self-Employed Driver by Sex

Note: Marginal predictions and confidence intervals of the model shown in column 1 in Table B3 in Appendix B. The regression controls for race, marital status, age, educational attainment level, presence of children in the household, and includes metropolitan and quarter fixed effects. Standard errors clustered at the metropolitan level.

Zooming into interactions between gender and demographic characteristics reveals interesting patterns. Based on theory, mothers face higher constraints to participate in the labor force by being the ones more likely to take on home production duties and, as such, more likely to benefit from the flexibility provided by ridesharing. The predictions shown in Figure 12 partly confirm the theoretical expectations: women in households with children ages 7 to 15 were more likely to be self-employed drivers in the after-ridesharing period, and so did those with no children. However, *women with younger children in the household did not observe significant changes – even when the household also included older children*. Hence, ridesharing does not seem to be valued as an alternative for women with young children. Meanwhile, men were more likely to drive regardless of the household composition. Interestingly, men with young children experienced the highest growth, suggesting that *fathers of young children may also prefer flexible arrangements*.

Differences were also observed regarding educational attainment levels (Figure 13). While individuals with a High School degree are the ones more likely to be self-employed drivers, those with a college degree or higher saw a disproportional increase in the post-ridesharing period, as seen in Chapter 2. Such an increase was even higher for women, as female College degree holders became the second group most likely to drive, contrasting with men, who have elementary school as second place. Overall, female drivers were more educated than males post-ridesharing.[18]

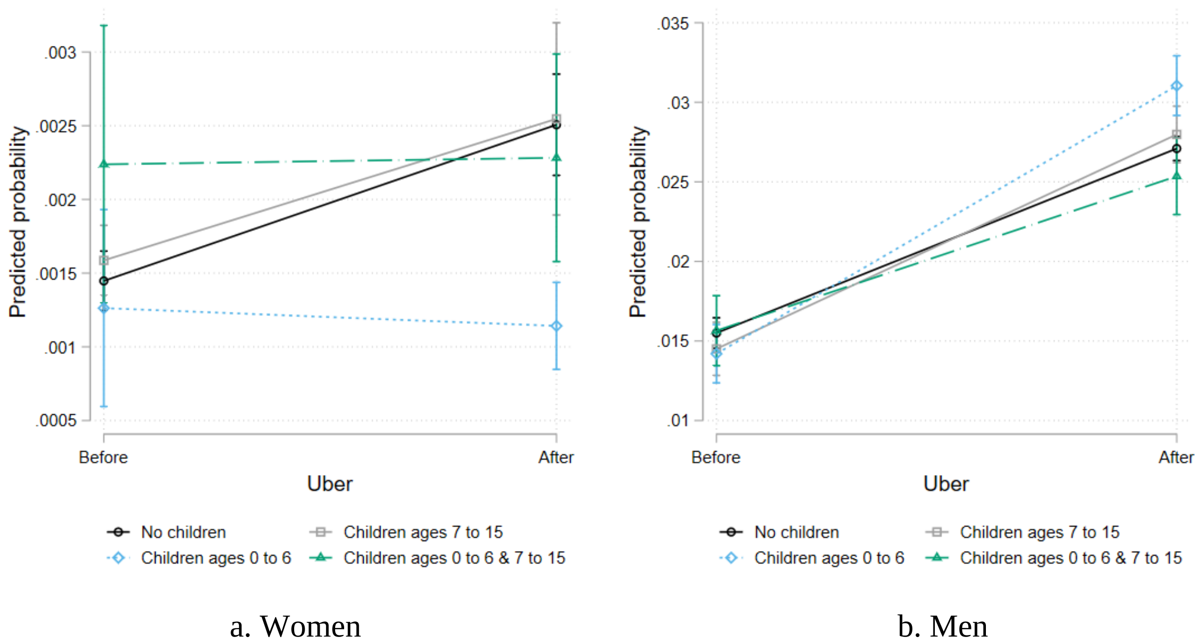
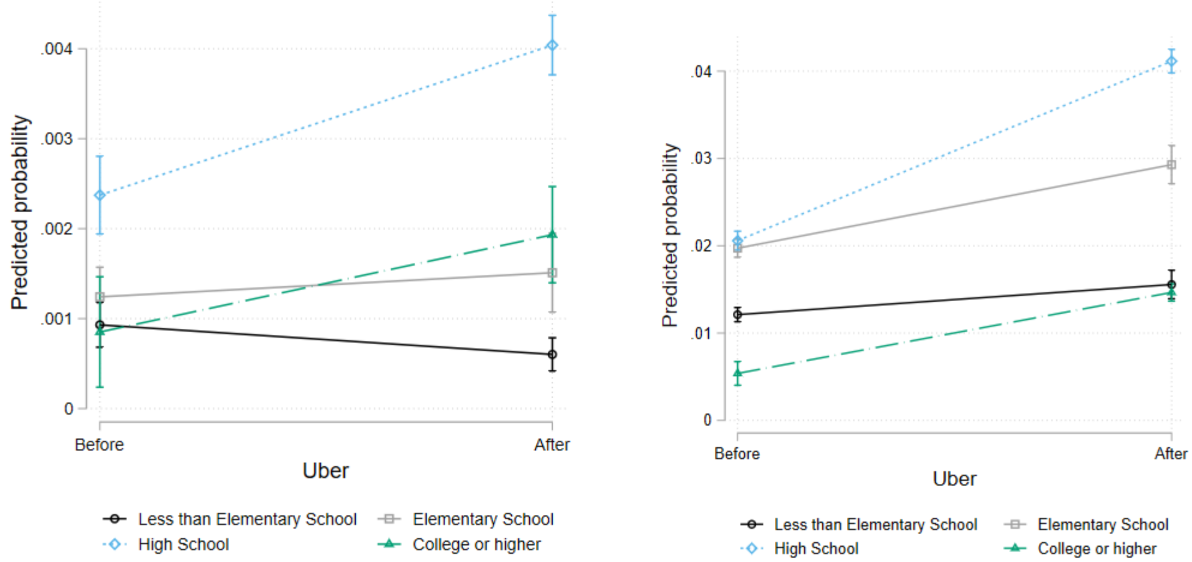


Figure 12. Predicted Probabilities of being a Self-Employed Driver by Sex and Presence of Children in the Household

Note: Marginal predictions and confidence intervals of models in columns 2 and 3 in Appendix B.

[18] Racial and marital status differences are not as striking (Figure B1 and Figure B2 in Appendix B). White individuals are more likely to drive in both periods, but black women and white men seem to have experienced a slightly higher growth in predicted probability than their counterparts. If these trends continue, racial differences will shrink for women, and increase for men. Trends in marital status are parallel for women, but single men are now equally likely to become a driver as married men in the post-ridesharing period.



a. Women b. Men

Figure 13. Predicted Probabilities of being a Self-Employed Driver by Sex and Education

Note: Marginal predictions and confidence intervals of models in columns 2 and 3 in Table B3 in Appendix B.

3.6.2 Effects of Violence

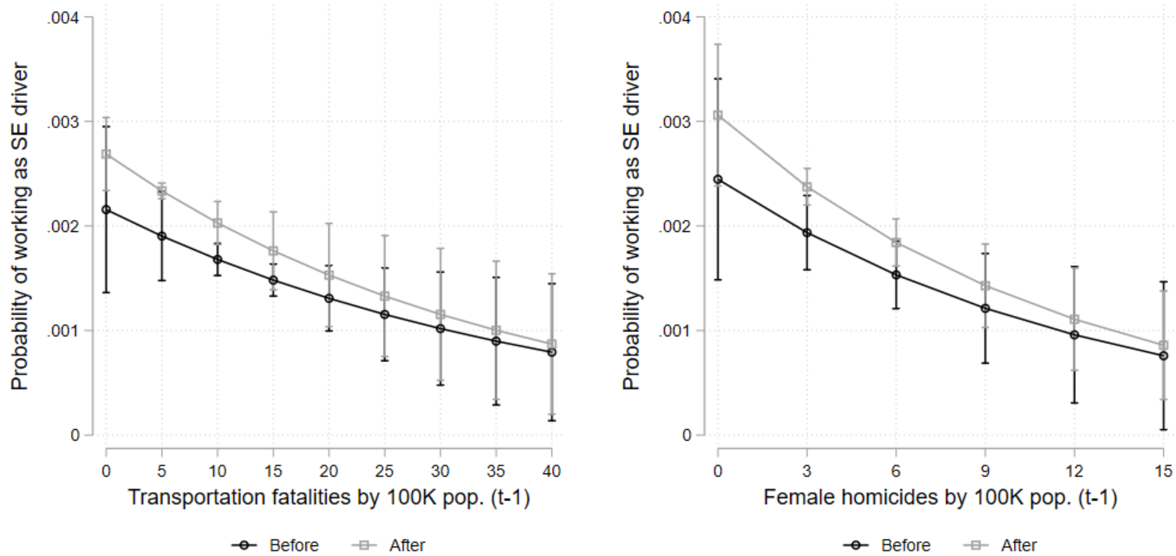
This section investigates the impact of violence as a mediator in the decision to become a self-employed driver. Table 7 provides the results of the logistic regressions estimated as in equation (2). Columns 1 and 2 show that one unit increases in fatalities in transportation reduces the log-likelihood of working as a self-employed driver by 0.03 for both sexes, holding the variables in the model constant. Interestingly, while workers are less likely to become drivers under bad traffic conditions, there is also evidence that ridesharing reduced transportation fatalities and hospitalizations in Brazil (Barreto, Silveira Neto, and Carazza 2021). Meanwhile, increases in female homicides reduce the log-likelihood of women driving by 0.08 but does not significantly affect men. Hence, *while all drivers are generally averse to risk of accidents,* *women also consider other forms of violence*. As suggested by the literature, safety concerns seem to be an important factor preventing higher female participation in ridesharing.

Table 7. Logistic Regressions of Self-Employed Driver

Variables	Men (1)	Women (2)	Men (3)	Women (4)
Uber	0.33***	0.18**	0.50***	0.25
	(0.07)	(0.09)	(0.08)	(0.17)
Transportation fatalities per 100k pop.	-0.03***	-0.03**	-0.02***	-0.03*
	(0.00)	(0.01)	(0.01)	(0.02)
Female homicides per 100k pop.	-0.03	-0.08**	-0.05*	-0.08*
	(0.03)	(0.03)	(0.03)	(0.04)
Uber * Transportation fatalities			-0.02***	-0.00
			(0.01)	(0.01)
Uber * Female homicides			0.02	-0.01
			(0.01)	(0.03)
Constant	-4.85***	-7.25***	-5.07***	-7.32***
	(0.25)	(0.47)	(0.21)	(0.55)
Observations	1,179,023	977,263	1,179,023	977,263
Pseudo R-squared	0.05	0.05	0.05	0.05

Note: All models include demographic characteristics and control for metropolitan and quarter fixed effects. Predicted probabilities from columns 3 and 4 are available in Figure 14 and Figure B3 (Appendix B), respectively. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Columns 3 and 4 test whether there has been any change in these relationships post-ridesharing. There is no evidence of changes of female responses to any of the violence forms captured in the model (Figure 14). As such, even though ridesharing data tracing mechanisms made it safer, they have not triggered different responses from women. Meanwhile, an interesting pattern emerges for men: in the post-Uber period, they are more likely to work as self-employed drivers than before until certain level of fatalities. However, as fatalities increase, their likelihood of driving reduces to pre-ridesharing levels (Figure B3 in Appendix B). Taken together, these predictions suggest that, for low levels of fatalities in transportation, male drivers in the post-ridesharing period are less risk averse than they used to be.



a. Transportation Fatalities

b. Female Homicides

Figure 14. Predicted Probabilities of Women being Self-Employed Drivers Before and After Uber

Note: Marginal predictions and confidence intervals of models in column 4 Table 7.

3.6.3 Changes in Job Outcomes

It has been shown that both men and women are more likely to work as self-employed drivers in the post-ridesharing period, but there are demographic nuances regarding who is more likely to do so. This section turns to the sample of self-employed drivers to investigate gender differences in earnings and hours of work.

Table 8 provides the regressions estimated as in equation (3). The coefficients on Uber show the expected earnings and hours of work of male drivers in the post-Uber period, the coefficients on female show differences relative to males, and the interaction coefficients show the difference in differences. Overall, male drivers earned less in total and hourly and worked fewer weekly hours in the post-Uber period than prior to Uber. Women's total earnings were less than men's in the pre-Uber period, but the gap has reduced in the post period. A similar trend is observed in hours of work. Hourly earnings were similar for men and women in the pre-Uber period, but the women experienced a gain after Uber. As a result, *while both groups experienced earnings losses, female drivers were less impacted*. Notably, this result reinforces the findings of IFC, Accenture, and Uber (2018) who identifies that ridesharing disproportionately boosts female income.

A natural extension of this analysis is to investigate heterogeneous effects by driver demographics. To examine that, models interacting Uber with demographic characteristics were run separately by gender.[19] In terms of household composition, the presence of children in the household affects the expected earnings and hours of work of women more than men's (Figure 15). However, the large confidence intervals resulting from the small sample of women, do not allow to reach significant conclusions. As an exception, women in households with children in both age groups had higher expected hourly earnings than women in households with no children. These mothers also seem to be the only group with an upward earnings trend, although the model cannot rule out that there has been no increase in hourly earnings relative to pre-Uber.

Another finding uncovered by the models is that the expected earnings (hourly and total) are higher for workers with college degrees (Figure B5). Such a finding is intriguing as, in principle, driving per se is not a job that would differentiate individuals by educational attainment levels. As such, it seems like the higher educated men and women found ways to work the system to their advantage. Alternatively, perhaps the higher educated individuals own better or newer cars, being more likely to benefit from the prices paid by premium services (e.g., Uber Black).

[19] Full results available in Table B5 and Figure B5 to Figure B7 in Appendix B.

Table 8. Demographic Characteristics and Job Outcomes of Self-Employed Drivers

Variables	Log. Monthly Earnings (1)	Log. Hourly Earnings (2)	Weekly Hours Worked (3)
Uber	-0.21***	-0.13***	-3.47***
	(0.02)	(0.02)	(0.67)
Female	-0.32***	-0.04	-11.04***
	(0.02)	(0.04)	(1.20)
Uber * Female	0.18***	0.11**	2.46**
	(0.03)	(0.05)	(0.94)
Black	-0.07***	-0.07***	-0.27
	(0.01)	(0.01)	(0.23)
Married	0.09***	0.05***	1.17*
	(0.03)	(0.01)	(0.68)
Age	0.00***	0.00***	-0.03
	(0.00)	(0.00)	(0.02)
Elementary School	0.17***	0.11***	1.86***
	(0.02)	(0.02)	(0.38)
High School	0.30***	0.22***	2.28***
	(0.01)	(0.02)	(0.46)
College or higher	0.47***	0.41***	1.80*
	(0.02)	(0.03)	(0.90)
Children ages 0 to 6 in the household	0.05	0.01	2.07***
	(0.03)	(0.03)	(0.62)
Children ages 7 to 15 in the household	0.03*	0.02	0.45
	(0.02)	(0.02)	(0.45)
Children (0 to 6) * Children (7 to 15)	-0.07**	-0.05	-1.01
	(0.03)	(0.03)	(1.04)
Constant	7.34***	2.03***	46.80***
	(0.02)	(0.03)	(0.74)
Observations	27,640	27,640	27,640
R-squared	0.16	0.12	0.05

Note: All models control for metropolitan and quarter fixed effects. Figure B4 in Appendix B illustrates the predicted job outcomes by gender. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

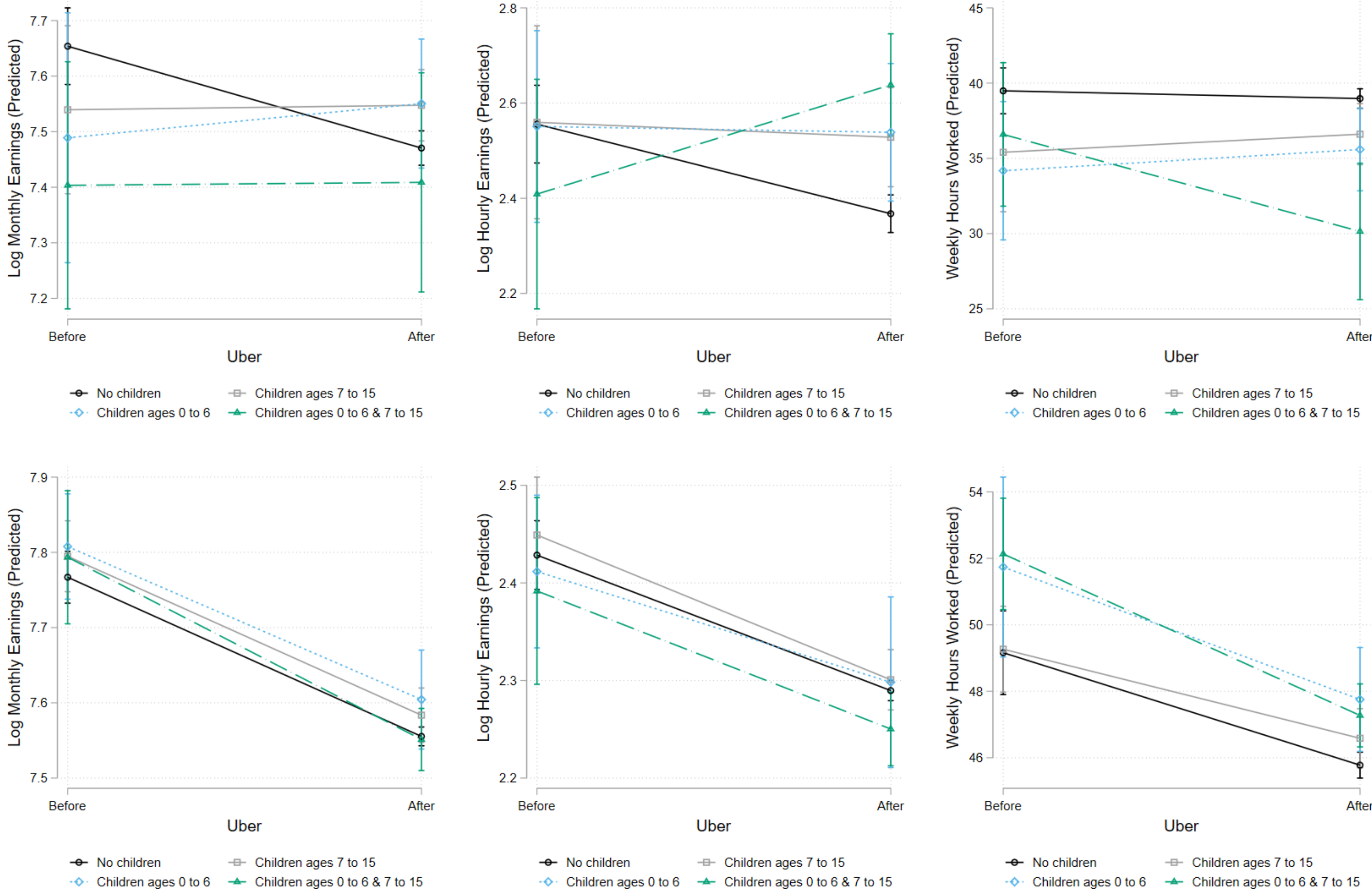


Figure 15. Predicted Job Outcomes by Sex and Presence of Children in the Household (Top panel: women. Bottom panel: men)

Note: Full models available in Table B5 in Appendix B.

There is no evidence of racial differences in job outcomes for women, but white men have higher expected earnings than comparable black men (Figure B6). Finally, married drivers have higher expected earnings than single drivers. Regarding hours of work, single women and married men are expected to drive for longer hours than their counterparts (Figure B7).

3.6.4 Spillover Effects: Labor Force Participation Rates

One of the reasons women exhibit lower labor force participation rates is their higher undertaking of household production duties. It follows that one expected effect of ridesharing, a flexible possibility, is to increase female labor force participation rates both directly and indirectly. Directly, women who were not in the labor force may rejoin it to become drivers. Indirectly, the ridesharing model has expanded to other sectors and became a complement service to other businesses. For example, the platform model has expanded to activities beyond transportation, such as delivery of food, groceries, and others. In doing so, it has been incorporated into the operations of existing industries, such as restaurants and retail, which may contribute to their expansion.

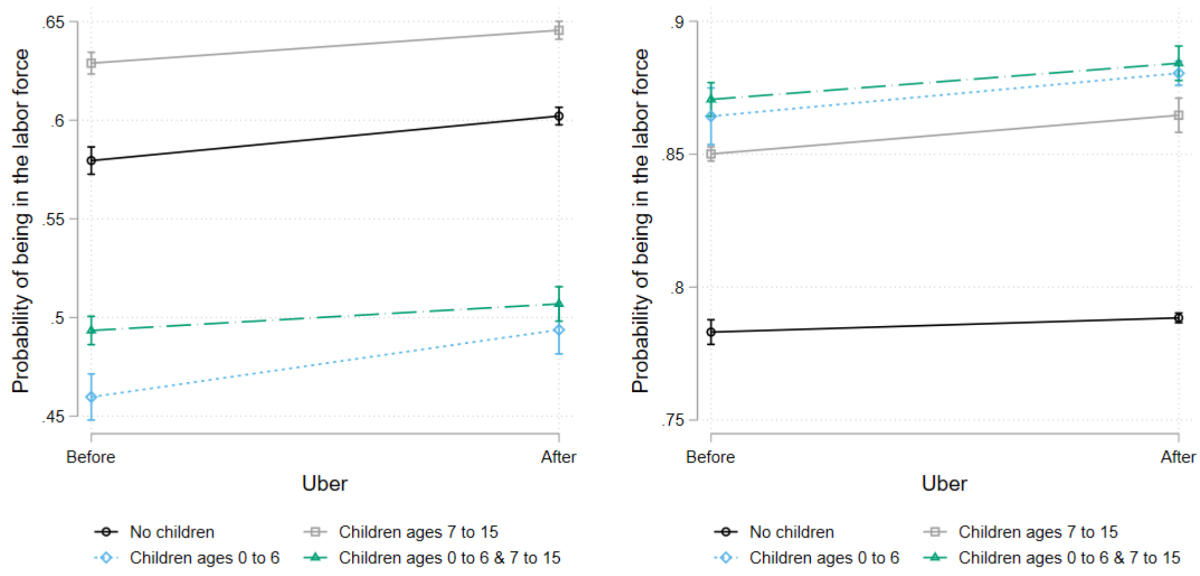
The models in Table 9 are logistic regressions, in which labor force participation is the dependent variable. As expected, there is a higher expected labor force participation rate in the post ridesharing period for both sexes, with a coefficient as twice as large for women relative to men. Women's and men's log odds of being in the labor force were, respectively, 0.12 and 0.06 higher in the post ridesharing period (columns 1 and 2).

Columns 3 and 4 investigate whether these increases revealed any patterns associated with the household composition. The predicted probabilities plotted in Figure 16 reveal that women with children ages 0 to 6 in the household (but not older) saw a disproportionately higher increase from 46.0 to 49.4 percent, although they are still the group with lower likelihood to be in the labor force. Hence, even though we did not observe a higher probability of becoming a self-employed driver for this group, ridesharing seems to have affected it indirectly.

Table 9. Logistic Regressions of Labor Force Participation

Variables	Men (1)	Women (2)	Men (3)	Women (4)
Uber	0.06***	0.12***	0.31***	0.39***
	(0.02)	(0.03)	(0.06)	(0.08)
Children ages 0 to 6	0.76***	-0.57***	0.68***	-0.59***
	(0.05)	(0.02)	(0.07)	(0.02)
Children ages 7 to 15	0.61***	0.24***	0.54***	0.25***
	(0.03)	(0.01)	(0.03)	(0.02)
Children ages 0 to 6 * ages 7 to 15	-0.56***	-0.13***	-0.48***	-0.09***
	(0.04)	(0.02)	(0.07)	(0.03)
Uber * Children ages 0 to 6			0.15**	0.04
			(0.07)	(0.03)
Uber * Children ages 7 to 15			0.11***	-0.02
			(0.02)	(0.02)
Uber * Children ages 0 to 6 * ages 7 to 15			-0.13**	-0.08***
			(0.06)	(0.03)
Constant	3.51***	2.13***	3.37***	1.98***
	(0.09)	(0.10)	(0.08)	(0.09)
Observations	1,631,322	1,959,989	1,631,322	1,959,989
Pseudo R-squared	0.20	0.15	0.20	0.15

Note: All models include demographics and control for metropolitan and quarter fixed effects. Uber interacts with all demographic characteristics. Predicted probabilities from columns 3 and 4 are available in Figure 16 and Figure B3 (Appendix B). Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1



a. Women b. Men

Figure 16. Predicted Probabilities of Being in the Labor Force Before and After Uber

Note: Marginal predictions and confidence intervals of models in column 4 in Table 9.

3.7 Conclusion

Ridesharing has emerged as both an opportunity and a challenge. As discussed in Chapter 2, ridesharing offered thousands of workers a job opportunity, but questions regarding job quality and worker protection remain a challenge. While the regulatory conundrum is yet to be solved, this essay is dedicated to understanding what types of workers were able to benefit from the emerging work arrangement. In particular, because women typically face higher labor force participation constraints and are theoretically more inclined to take flexible jobs, theory suggests that ridesharing may represent a different opportunity for men and women.

Were women more likely to become drivers after the emergency of ridesharing than men? Were mothers – the group of women with higher constraints – able to take the ridesharing opportunity? If so, were their gains and work schedule similar to men’s? If not, what factors may have prevented them from doing so? This chapter provides insights into many of these questions in the Brazilian context. Building on the staggered rollout of Uber in Brazil, this study focused on between and within sex differences in the likelihood of becoming a self-employed driver, job outcomes, and labor force participation rates.

The results show that while there has been an enormous increase in the number of female drivers, the occupation remained dominated by men. Safety concerns seem to be one of the factors preventing women from driving more, and the results uncovers that, while both sexes are equally averse to violent traffic, women also (and strongly) respond to female homicide rates. Such a finding highlights violence as an invisible structural inequity preventing women from taking advantage of this job opportunity.

Additionally, the household composition respective to the presence of children showed up as an essential variable shaping women's probability of becoming drivers. All men were more likely to drive regardless of household composition, but only women without children or with older children saw increased probabilities. Unlike the theoretical expectation, mothers of young children in Brazil were not more inclined to drive after Uber than they were before it.

In terms of job outcomes, the results show a reduction in the gender pay and schedule gaps driven by a reduction in males' earnings and hours of work in the post-ridesharing period. Hence, as suggested by prior literature, women gained a greater boost from ridesharing than men (or, in this case, a lower loss). Within women, mothers had higher expected hourly earnings than those with no children in the post-ridesharing period.

The results also show that ridesharing increased female labor force participation at a much higher rate than men. Mothers of young children, specifically, were the ones who saw a higher increase in the probability of being in the labor force from 46.0 to 49.4 percent before and after ridesharing. I argue that such increases are both *directly and indirectly* favored by ridesharing by providing a job opportunity and complementing other sectors of the economy. Although various studies have explored the impacts of ridesharing on the taxi sector (Cramer and Krueger 2016; Berger, Chen, and Frey 2018; Resende and Lima 2018), its linkage effects with other sectors in the economy are a worth-studying area that has not received much attention yet.

Taken together, the results show that ridesharing indeed impacted women differently than men. Moreover, had women had fewer constraints to working as drivers, including safety concerns, they could have been able to take even more advantage of the flexibility offered by ridesharing. Such a finding sheds light on equity considerations beyond ridesharing in Brazil and uncovers the need to improve the ridesharing space so that more women feel safe to participate. Indeed, there is evidence that the women who did so were able to disproportionately benefit from platforms (IFC, Accenture, and Uber 2018).

Finally, while this study shows important gains and benefits of ridesharing to women, it does not intend to distract from the concerns related to job security and quality. Instead, it reinforces the need to regulate the system so that all participants, drivers and riders, can be better off. A safer ridesharing system with better earnings and worker protections would be even more beneficial to women, contributing to reduce labor inequities.

Chapter 4: Preference for Flexibility of Workers in Online Platforms: An Experimental Exploration[20]

4.1 Introduction

A common assumption regarding motivations to be a platform worker is a desire for flexibility. While a few studies have successfully measured preference/use of flexibility for Uber drivers (K.-M. Chen et al. 2020; M. K. Chen et al. 2019), far less evidence is available to other platform settings beyond ridesharing. However, it is unclear to what extent findings from ridesharing apply elsewhere in the platform economy.

Surely, most platform workers share common features such as the platform as a medium, and jobs that consist of multiple independent tasks. Under the surface, research continues to uncover variations within and across platforms in terms of rules and outcomes, and the typical workers within them (Ravenelle 2019; 2017; Vallas and Schor 2020). For example, in some labor platforms, the task is location-based and must be executed in a specific place and time, as in the case of ridesharing. In other cases, as in *cloud work*, the task is non-location based and can be executed remotely via the internet. Within cloud work, some platforms distribute tasks to individuals by order of acceptance and for the same payment per task (*crowd work*), whereas in others, workers market themselves, and are hired based on their skills or portfolio for a negotiated payment (*freelance marketplaces*) (Schmidt 2017). As our attention shifts to these details, cloud workers become increasingly distant from ridesharing drivers, underlining the need for targeted studies.

This chapter focuses on workers providing services in the cloud work setting in the United States, their preferences, and motivations. Freelance marketplaces represent a sizeable

[20] This chapter has been generously supported by an Andrew Young School Dissertation Fellowship.

and growing workforce that grants specific attention. Indeed, estimates suggest that the freelance workforce in the country totaled 57 million people in 2018 and trending up (Freelancers Union and Upwork 2018).

This study contributes to clarifying these matters by combining an online experiment – that captures *revealed* preference for flexibility – with a survey, which gathers further information on motivations and preferences of platform workers.[21] The data was collected from a random sample of workers selected from one of the largest freelance marketplaces in the country: Fiverr. Operating in over 160 countries and having more than a million freelancers, Fiverr is the world largest marketplace for digital services (Apostolicas 2021). Workers were grouped by their degree of reliance on platform earnings into low- and high-reliance, as there is evidence that the extent to which workers *de facto* enjoy flexibility – even within platforms – depends on how much they need the platform gains to cover essential needs (Schor 2020).

The experiment comprises two phases, one week apart from each other. In phase I, subjects select a time slot for participation in the upcoming week, in which choices vary between getting a random time slot or choosing between flexible options (at a cost). As such, the decision of when to participate provides an upfront and observational measure of preference for flexibility. In Phase II, respondents participate in an online sequential choice under risk experiment and a multiple price list task – to collect further information on their preferences.

The observation of preferences in an experimental setting has immediate relevance for policymaking. In the context of increasing labor de-regulation and the growth of platform work, it becomes essential to distinguish whether workers rely on platforms by intrinsic motivations or the lack of other opportunities. If there is evidence that workers are intrinsically motivated by

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[21] The research protocol has been approved by the Georgia State University Internal Research Board on July 07, 2021 (IRB protocol #366076).

preferences, platforms improve labor market matching. However, if that is not the case, understanding motivations is even more critical as workers may be pushed by external constraints, such as unemployment or primary jobs that are insufficient to make ends meet.

This essay presents initial findings from a data collection process that will continue in the future. The preliminary results indicate a positive correlation between preference for flexibility and reliance on platform income, suggesting that workers are drawn to the platform due to their inherent preferences. The advantages of the platform, including various forms of flexibility and potential scale gains, are consistently highlighted by the participants. Notably, all current participants rely on platform earnings to cover at least half of their basic family expenses. However, even within this positive context, concerns related to insecurity and uncertainty are expressed as perceived disadvantages. As this research progresses and gathers more data, it will provide greater clarity on whether the findings from the sample can be confidently extrapolated to the wider population of freelancers.

4.2 Literature Review

4.2.1 Flexibility

Preference for flexibility was first conceptualized by Kreps (1979) as a preference for larger menus when the choice is to be realized in the future, and the costs are uncertain. For example, if an individual is unsure about what she will wish to eat for dinner, she would rather make a reservation at a restaurant with a menu that offers more choices than a single dish.

While this understanding of preference for flexibility as a predilection for larger choice sets is easily translated into the platform context, in practice, these menus can appear in various forms. Indeed, flexibility may entail different aspects, for example, the autonomy to make one's own decision regarding when and where to work, and the ability to adjust these decisions without many constraints in a reasonable time frame (variable by platform context).[22] In some platforms, as in freelance marketplaces, workers also have the flexibility to choose which jobs to take, representing a potentially broader choice menu than what is available at a typical job. Importantly, both the desirability for these many flexibilities and the ability to *actually* benefit from them varies in the workforce. For example, women with young children seem to value working from home and avoiding irregular schedules more than schedule flexibility itself (Mas and Pallais 2017). Meanwhile, workers who rely on platform earnings to cover their basic expenses are less likely to benefit from the perks of flexibility, as further discussed in section 4.2.2 (Schor et al. 2020).

These caveats aside, although flexibility is often claimed as one of the greatest advantages of platform work, only a handful of studies have attempted to directly estimate its value. In these studies, flexibility is usually conceptualized as some version of the ability to make almost instantaneous decisions regarding whether and how much to work.

For example, two studies on ridesharing in the United States find flexibility to be a central component of the drivers' compensation. In the first, M. K. Chen et al. (2019) use variations in reservation wages to estimate the driving surplus derived from flexibility (defined as the ability to choose when to supply labor on a minute-by-minute basis). Their results show larger surpluses in ridesharing than in less flexible arrangements, robust to a series of tests. Likewise, K.-M. Chen et al. (2020) capture the value of flexibility defined as the ability to i) set a

[22] Platforms allow a faster decision making than traditional jobs, but the adjustment speed vary across platform contexts. For example, in ridesharing the decision-making is almost instantaneous: drive or not drive, accept or not a ride. However, in freelance marketplaces, orders are typically negotiated between sellers and buyers and once agreed upon, have specified deadlines to be fulfilled. Thus, the decision-making in freelance marketplaces is longer as compared to ridesharing.

customized work schedule and ii) adjust the schedule from day-to-day and hour-to-hour in response to unexpected changes in offered wages or driving costs. In both cases, flexibility is found to be a central component of the total compensation. Interestingly, reservation wages of infrequent drivers are much higher than of full-time drivers, suggesting a stronger reliance on the platform income by the latter and, consequently, a *reduced possibility to take advantage of the real time flexibility*.

The high preference for instantaneous decision-making may be a characteristic of the ridesharing labor market. In an experiment with a different set of workers, Mas and Pallais (2017) advertised call-center job offers in several metropolitan areas in the United States, offering applicants the choice over contracts with varying degrees of flexibility. From estimated compensating differentials – and in contrast to the ridesharing literature – they found that most workers do not value choosing how many or which hours they work. Instead, they value working from home – women even more than men – and the average worker is willing to give up 8 percent on wages to have that option. Workers are also averse to arrangements in which the employer has discretion over their work schedule, which seems to come mainly from the aversion to working on weekends and evenings – and the average worker is willing to give up on 20 percent of wages to avoid this possibility.

In the cloud work setting, Dean and McNeill (2020) studied preference for flexibility among MTurk workers. Preference for flexibility is defined as an outcome of preference uncertainty in the sense of Kreps (1979). In the experiment, subjects chose between real-effort task menus to be implemented at distinct times in the future, in which one of the options represented a flexible contract. Although the tasks are similar across menus (arithmetic problems), there are variations in how much of a task had to be accomplished for a contract to be considered fulfilled, and at different rates.[23] Results suggest that many subjects exhibit a strict preference for flexibility (or were willing to pay a positive amount to have the flexible option), and that such a preference translates into *effective* use of flexibility. Therefore, rather than a heuristic preference for larger sets, preference for flexibility is related to preference uncertainty, and translates into real use of the flexible option. To the best of my knowledge, Dean and McNeill (2020) provide the only study that measured preference for flexibility in a cloud work setting and, as such, it is the one that more closely relates to this.

However, MTurk findings do not necessarily translate to Fiverr. In the former, tasks that are not given to specific workers, but distributed by order of acceptance and for the same pay whereas in the latter, tasks are given to specific individuals, who are chosen based on their skills or portfolio, and payment is negotiated based on the task (Schmidt 2017). Therefore, worker bargain power and preferences are expected to vary across settings, and understanding these variations requires empirical investigation.

4.2.2 Income Reliance and Platform Jobs as Primary or Secondary Sources

As discussed in the previous chapters, some workers have joined platforms as their full-time jobs while others use them as a supplemental income source. Distinguishing between these groups has direct practical implications, as it relates to the degree of reliance on platform income.

Overall, reliance on platform income seems to be an important antecedent variable explaining worker experience and job outcomes (Schor et al. 2020; Dunn 2020; Myhill,

[23] In short, there were three contract options: at the low contract, workers would complete a reduced number of tasks for a lower payment. In the high contract, workers had to perform a higher number of tasks but for a higher payment. Finally, in the flex contract, workers could perform either a low number of tasks for a lower payment, or a high number of tasks for a higher payment.

Richards, and Sang 2021; Berger et al. 2019). Workers who rely on platforms as a secondary source are more likely to have access to labor protections and a steady income source (from the main job). Likewise, those who do not depend on platform income to cover basic expenses find themselves in a position in which choosing what jobs to take and when to work is a realistic possibility. This translates into supplemental earners being more satisfied, having higher *hourly* wages, and being more likely to enjoy the perks of autonomy and flexibility in platforms than dependent earners (Schor, 2020).

Given these implications, the motivations that lead to platform work as a primary or secondary job likely differ across groups and must be considered separately from a theoretical standpoint. Full-time platform workers may either have a preference for this work arrangement or be temporarily on it given the lack of alternatives elsewhere. Or, borrowing concepts from the literature on entrepreneurship, individuals may end up working in platforms due to intrinsic motivations (*pull factors* such as preferences), or due to other circumstances that push them in that direction (*push factors* such as unemployment) (Benedict and Hakobyan 2008; Hughes 2003). The over emphasis on preferences, including preference for flexibility, tends to cover the second motivator, even though the implications of each are entirely opposite.

To understand the second group's motivations – platforms as a secondary income source, the literature on dual job holding is a natural starting point. Traditional motivations for moonlighting include a constraint on the first job, such as a restriction in the maximum number of hours (constrained workers), and the goal to obtain a job portfolio (non-constrained workers) (Renna and Oaxaca 2006; Hirsch, Husain, and Winters 2016).

Job portfolios may be desirable for an infinitude of reasons, such as searching for a better combination of pecuniary and nonpecuniary benefits. For example, workers may have a higher preference for job differentiation and use multiple jobs to increase the diversity of tasks. Likewise, they may be averse to risk and use multiple jobs as a form of insurance to cope with income fluctuations in the main job. Insurance may also be used if the worker is looking for a new job but not willing to give up on the first before finding a good match, and a second job allows testing options under a less risky and costly search environment (Renna and Oaxaca 2006; Hirsch, Husain, and Winters 2016). In practice, distinguishing between portfolio and constrained workers' motivations is a challenge for empirical studies.

Assessing whether traditional motivations for dual job holding apply in the platform context requires an empirical investigation. It seems to be the case that they do still apply for workers using MTurk as a second job but varying by gender (Doucette and Bradford 2019). Constraints on hours at the main job seem to be an important motivator for men to join MTurk, but it is much less so for women who, instead, showed much concern with the job security at the first job. However, once again, it is unclear the extent to which these findings are externally valid beyond crowd work.

4.3 Research Question and Hypotheses

This chapter's central question regards whether workers in freelance marketplaces reveal a preference for flexibility, and how these vary based on platform reliance. More specifically, the goal is to test if dependency on platform income translates into differences in observed preferences for flexibility and perceptions of the platform. While acknowledging that flexibility entails various elements, this study does not intend to distinguish these. Instead, it proposes various measures that jointly allow capturing the revealed preference. For example, in the experimental setting, discussed in section 4.4.1, participants are asked to choose between options that capture preferences for autonomy, uncertainty, and risk aversion – all of which speak to the concept of flexibility in some way.

Under the assumption that platform jobs are less secure than standard jobs, workers relying on them as their primary income source are expected to have higher preference for flexibility than workers relying on these to supplement income. If that turns out not to be the case, perhaps full-time platform workers are not motivated by intrinsic preferences. While the experiment does not allow to definitively disentangle these alternative pathways, survey questions allow exploring them in more detail.

4.4 Empirical Strategy

The study comprises three phases, as follows:

- Pre-experimental phase: Data scrapping from Fiverr to characterize the universe and draw a representative sample of workers.
- Experiment phase I: Subjects randomly selected from the web-scrapped universe are invited to participate through direct messages. Subjects receive a link to the study, in which they must choose a time to participate in phase II. The choices vary by degree of flexibility and, therefore, provide an upfront measure of preferences.
- Experiment phase II: One week after phase I, subjects participate in a sequential choice under risk experiment, followed by a multiple price list task and a survey. This phase gathers observational and self-reported data on preferences and motivations.

The software for phases I and II was developed in oTree (D. L. Chen, Schonger, and Wickens 2016).

4.4.1 Pre-Experimental Phase: Sample Definition and Selection

Workers (henceforth, sellers) find jobs (henceforth, gigs) through Fiverr by posting gig offerings. Each gig has its own webpage containing information such as service description, starting fees, examples of prior work, reviews, and information about the seller. Fiverr allows buyers to browse for gigs but not for specific sellers. For example, one can search for "web-scrapping" but not for usernames such as "scrapper34." Hence, this study began with an analysis of gigs. The strategy adopted included the following steps: identify all service categories, web-scrape as many gigs as possible, use the scrapped data to define the universe of sellers, generate a stratified representative sample, and, finally, invite sellers to participate.

The Fiverr Gig's Directory webpage was used to identify the services provided in the platform. By February 2023, there were a total of nine service categories containing 233 subcategories.[24] The second step – web scrapping – consisted of gathering data from gigs listed in all 233 subcategories, filtering the results by sellers who lived in the United States and spoke English.[25,26]

The web-scrapping resulted in a dataset containing the following variables for over 145 thousand gigs: webpage link, seller username, starting fee, and main service category (Table C1 in Appendix C). The username variable allowed narrowing gigs down to the seller level, and a second web-scrapping procedure occurred to collect two additional variables at the seller level:

[24] Categories, subcategories, and sub-subcategories are available at: https://www.fiverr.com/categories.
[25] A seller on Fiverr was hired to perform the web-scrapping, and the service was completed between February 7 and 17, 2023.
[26] One challenge in the web-scrapping process was imposed by the website structure: Fiverr lists up to twenty pages of results with 48 gigs in each, totaling 960 gigs per search. Most of the 233 subcategories had fewer than 960 gigs listed after applying the filters, and it was possible to extract data on all of these. However, 40 subcategories had more and extracting the entire data was unfeasible. In these cases, sorting by "best sellers" and "new arrivals" was used as a strategy to maximize the data gathering.

date in which they became Fiverr members, and the last date they completed an order.[27] Last completion dates were used to identify active sellers, and starting fees provided reference prices to define dominant rewards.

In addition to only including sellers who spoke English and lived in the United States, two additional inclusion criteria were adopted. First, only sellers offering services in a single category – 87.2 percent of the total – were kept in the data to allow a stratified sample selection strategy. An additional concern was to ensure that the final seller dataset only included individuals who were active in the platform, in which *active* was defined as having completed a service since January 2023. Because income reliance is a key variable of interest, sellers who have not gained earnings from the platform recently or ever are not eligible to this study.[28]

Table 10. Summary of Web-Scrapped Data

Category	Total of sellers	Sellers (%)	Median starting fee	Mean starting fee	Mean gigs per seller
Writing & Translation	4,384	27.1	20.0	46.4	3.0
Graphics & Design	3,280	20.3	20.0	46.6	2.6
Music & Audio	3,036	18.8	25.0	43.1	2.4
Lifestyle	1,408	8.7	15.0	27.0	3.0
Digital Marketing	1,184	7.3	25.0	79.1	2.6
Programming & Tech	936	5.8	50.0	150.9	3.7
Business	906	5.6	40.0	88.3	4.0
Video & Animation	895	5.5	25.0	72.3	2.5
Data	133	0.8	25.0	92.5	2.1
Total	16,162	100.0	20.0	56.7	2.8

The final dataset of eligible workers – active sellers offering services in a unique category who spoke English and lived in the United States – comprised 16,162 individuals, as summarized

[27] The second extraction was complected between March 6 and 28, 2023 by the same Fiverr seller who conducted the previous web-scrapping. Individual sellers webpages follow the structure “https://www.fiverr.com/sellername”.
[28] Overall, the data shows a surprising number of sellers who have no delivery history in their profiles (about 50 percent). However, for those who did have a delivery date, 78.0 percent had a last delivery completed somewhere between January-March, and 76.9 percent in March itself.

in Table 10. Together, the three largest categories, writing and translation, graphics and design, and music and audio, account for 66.2 percent of all sellers. Starting fees vary across the nine service categories, being higher at Programming and Tech, and Business. As the starting fees distribution are extremely skewed towards Fiverr's minimum fee ($5), the median and mean values differ significantly in total and within each category (see Figure C1 in Appendix C for the full distribution). Since the median is a better central tendency measure in skewed distributions, it is adopted as a reference to define dominant rewards in the experiment, which were set to range between 8 and 45 dollars.

Once the pool of eligible workers was defined, the last step consisted in selecting a random sample to be invited to participate. The sampling process followed a proportionate stratification by subgroups strategy based on the nine Fiverr service categories. Between May 8 and 12, a total of 195 sellers were invited to participate in the study, equally distributed across categories (Figure C3 in Appendix C). Messages were sent from Monday to Friday, inviting sellers to participate in the study on the same weekday in the following week, and were set to expire at midnight of the day after the invite.[29] Links to the experiment page and unique access codes were provided to sellers who made it to the final sample.

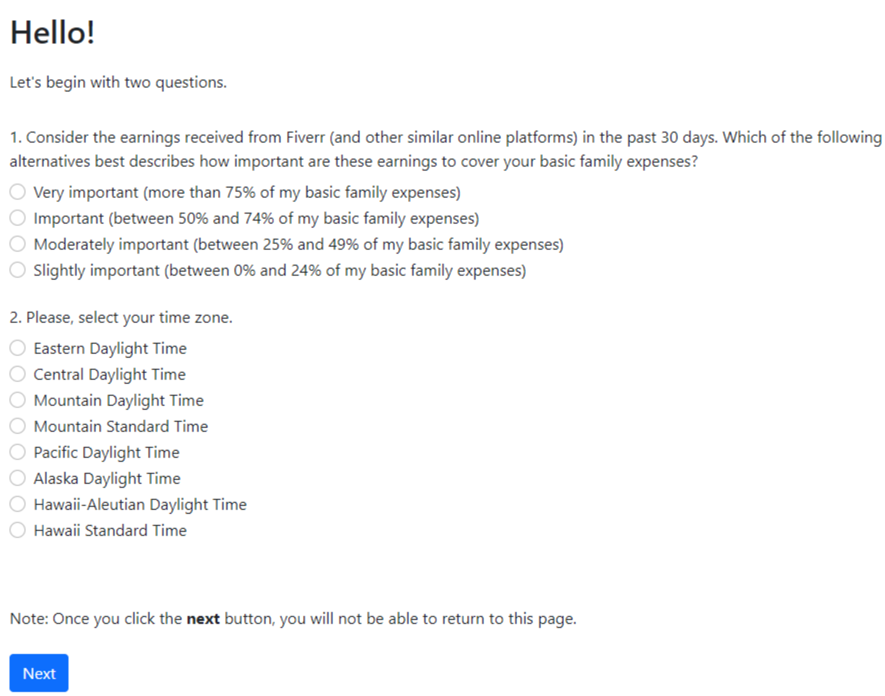
4.4.2 Phase I

Once recruited, participants were redirected to Phase I. Here, the task was to decide when to participate in Phase II from three options: receive a random slot for a $5 bonus, pick one slot of their choice, or get a full-day long slot to participate for a $5 cost (Figure 18). These options increasingly trade flexibility for earnings, in which picking one's own slot costs 5 dollars (as a

[29] For example, invitations sent on May 8 corresponded to a study occurring on May 15, and sellers could register until May 9 at midnight.

forgone bonus) relative to the random slot and having the full day costs 10 dollars (forgone bonus plus fee). As such, participant choices provide an upfront and real-world context measure of their preference for flexibility.

In addition to booking a slot for participation, in Phase I subjects also were asked their time zone to ensure they received time compatible links, and their degree of reliance on the platform income, which is central for the study (Figure 17). Time slots included two options in the morning (9:30-10:30 and 10:45-11:45), two in the afternoon (2:00-3:30 and 3:45-4:45), and two in the evening (7:00-8:00 and 8:15-9:15). The most flexible option ranged from 9:30 am to 9:15 pm. Slots were larger than the expected time for completion (20 minutes) to allow for subject delays and technical issues, and they were spread throughout the day to allow subjects with constrained hours to participate.



Hello!

Let's begin with two questions.

1. Consider the earnings received from Fiverr (and other similar online platforms) in the past 30 days. Which of the following alternatives best describes how important are these earnings to cover your basic family expenses?

- Very important (more than 75% of my basic family expenses)
- Important (between 50% and 74% of my basic family expenses)
- Moderately important (between 25% and 49% of my basic family expenses)
- Slightly important (between 0% and 24% of my basic family expenses)

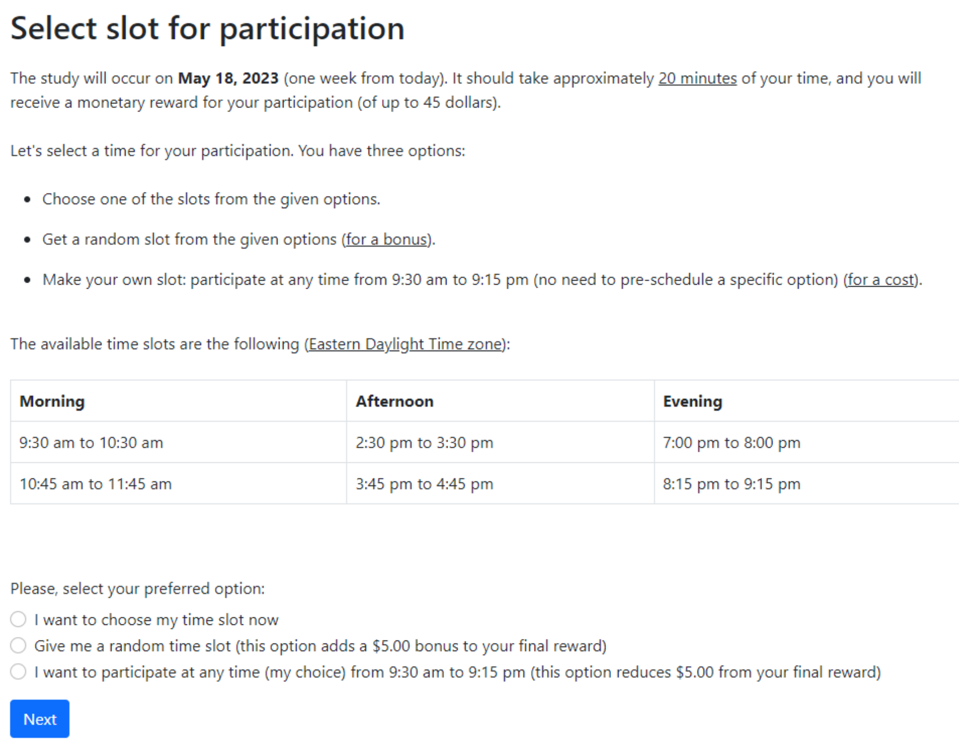
2. Please, select your time zone.

- Eastern Daylight Time
- Central Daylight Time
- Mountain Daylight Time
- Mountain Standard Time
- Pacific Daylight Time
- Alaska Daylight Time
- Hawaii-Aleutian Daylight Time
- Hawaii Standard Time

Note: Once you click the **next** button, you will not be able to return to this page.

Next

Figure 17. Additional Questions in Phase I



Select slot for participation

The study will occur on **May 18, 2023** (one week from today). It should take approximately 20 minutes of your time, and you will receive a monetary reward for your participation (of up to 45 dollars).

Let's select a time for your participation. You have three options:

- Choose one of the slots from the given options.
- Get a random slot from the given options (for a bonus).
- Make your own slot: participate at any time from 9:30 am to 9:15 pm (no need to pre-schedule a specific option) (for a cost).

The available time slots are the following (Eastern Daylight Time zone):

Morning	Afternoon	Evening
9:30 am to 10:30 am	2:30 pm to 3:30 pm	7:00 pm to 8:00 pm
10:45 am to 11:45 am	3:45 pm to 4:45 pm	8:15 pm to 9:15 pm

Please, select your preferred option:

- I want to choose my time slot now
- Give me a random time slot (this option adds a $5.00 bonus to your final reward)
- I want to participate at any time (my choice) from 9:30 am to 9:15 pm (this option reduces $5.00 from your final reward)

Next

Figure 18. Participation Slot Options in Phase I

4.4.3 Phase II

Phase II comprises two choice-under-risk experiments, and a survey. The experiments relied on induced valuation to incentivize participants to reveal their preferences, and rewards were defined considering salience and dominance criteria. The first experiment consists of three rounds of choices between two contracts to be realized in an unknown future. In every round, contract A trades 40 units of a good for a given price (in points). Contract B also has a fixed price in each round, lower than A's, but subjects can choose the number of units to trade (0 to 40) once they know the future state of the world. The roll of a ten-sided die determines states of the world after subjects choose their contracts. In 80 percent of the time, the state is normal and there are no unexpected costs. However, in the remaining time, the state is atypical, and the subject needs to pay a fee for every unit sold above 35, which varies across rounds. Figure 19 illustrates the main decision page in the web environment.

In this set up, contract A represents the standard option and contract B the flexible option. Flexibility in adjusting for unexpected futures (atypical states) is increasingly costly across rounds. Table 11 illustrates the parameters for this game, in which p is the price of each contract, q is the quantity of units sold (fixed at 40 for contract A, and flexible for contract B), and c is the costs changed for each unit above 35 in atypical states.

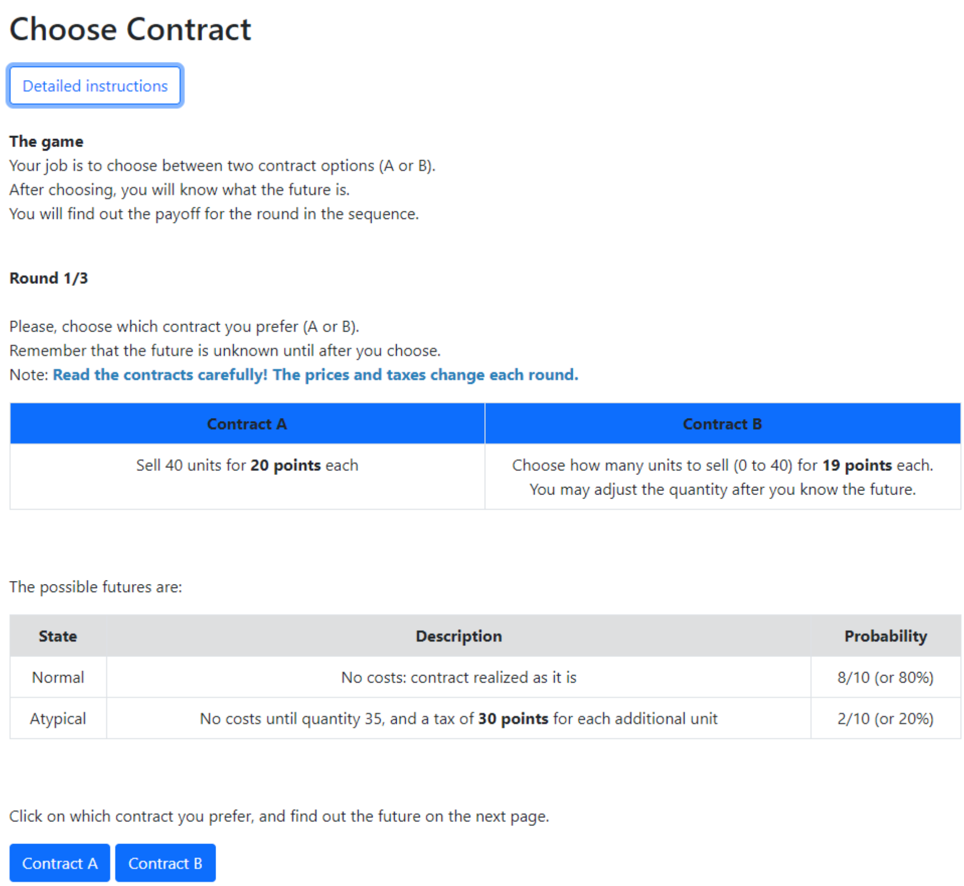


Figure 19. Decision Page, Experiment 1 in Phase II

Table 11. Parameters and Expected Payoff in Experiment 1 in Phase II

Round: cost	A	B	Difference (A-B)
1: c=30	q=40, p=20	p=19	
Payoff (normal)	800	760 (q=40)	40
Payoff (atypical)	650	665 (q=35)	-15
EV	770	741	29
3: c=35	q=40, p=15	p=14	
Payoff (normal)	600	560 (q=40)	40
Payoff (atypical)	425	490 (q=35)	-65
EV	565	546	19
2: c=50	q=40, p=25	p=24	
Payoff (normal)	1000	960 (q=40)	40
Payoff (atypical)	750	840 (q=35)	-90
EV	950	936	14

The second experiment is a multiple price list (MPL) task, a standard measure of risk aversion which is used here to capture preference for flexibility. Subjects need to choose between two lotteries across ten rows, in which lottery A is less risky than lottery B (Figure 20). Across the rows, the expected value of lottery A is larger than lottery B until row 5, when they are equal, and lower from row 6. A risk-neutral subject is expected to prefer A until row 4, be indifferent in row 5, and switch to lottery B afterward. Subjects with risk-taking behavior are expected to prefer lottery B before the equal payoff row.

The final compensation for participation in the study is the sum of i) Phase I bonus or penalty, if applicable and ii) a random round in Phase II converted from points to US dollars at a 25:1 rate. Added the bonus/penalties and survey, the minimum and maximum payments are within $8 and $45, which seem to be dominant in the context of Fiverr, and considering the time expected for completion.

Part II

For each of the rows below, please click on the lottery you prefer (A or B).

You will only be able to go to the next page once a lottery has been **clicked in each row**.

On the next page, one of your choices will be randomly picked and played.

Example of how to read the lotteries: In row #1, if you choose Lottery A, and the die number is 1, your payment will be 600 points. However, if the die number is anything from 2 to 10, your payment will be, instead, 400 points. Alternatively, if you choose Lottery B in row #1, your payment will be 800 points if the die number is 1, and 200 if the number is anything between 2 and 10.

Row #	Lottery A	Lottery B
1	1 = 600, or 2-10 = 400	1 = 800, or 2-10 = 200
2	1-2 = 600, or 3-10 = 400	1-2 = 800, or 3-10 = 200
3	1-3 = 600, or 4-10 = 400	1-3 = 800, or 4-10 = 200
4	1-4 = 600, or 5-10 = 400	1-4 = 800, or 5-10 = 200
5	1-5 = 600, or 6-10 = 400	1-5 = 800, or 6-10 = 200
6	1-6 = 600, or 7-10 = 400	1-6 = 800, or 7-10 = 200
7	1-7 = 600, or 8-10 = 400	1-7 = 800, or 8-10 = 200
8	1-8 = 600, or 9-10 = 400	1-8 = 800, or 9-10 = 200
9	1-9 = 600, or 10 = 400	1-9 = 800, or 10 = 200

Submit

Figure 20. Decision Page Experiment 2 in Phase II

Phase II concludes with a survey that gathers data on workers experience in the platform, including how long they have been using it, and for how longer they expect to continue to do so, how many hours they usually dedicate to platform work and other jobs (if any), their reasons for enrolling, and perceptions of greatest advantages and disadvantages. The survey also collects some demographic variables (gender, race, educational attainment levels, age, marital status, and presence of children in the household) to better assess the workers' profiles, and to allow comparisons across demographic variables of interest. Figure C4 and Figure C5 in Appendix C illustrate the survey interface. Upon completion of the survey, participants are promptly informed about their final compensation, and instructed to generate an order through Fiverr to receive their reward.

4.4.4 Implementation Challenges

A challenge encountered during the invitation process was the perception that the invitation was not legitimate by many sellers – a distrust that is not unexpected given the level of scams on the internet nowadays. When questioned, detailed answers were provided to the sellers about the legitimacy of the study, the researcher, and the research process. However, many sellers reported the invitation without allowing room for clarifications. A total of 36 subjects accepted the invitation to participate – about 18.5 percent of the invitations (Table 12). Plausibly, this group is less risk averse than the nonrespondents.

Due to the time span between phases I and II, attrition was another expected challenge. To mitigate this issue, reminders were sent to the subjects via the Fiverr chat one day prior to the scheduled time for Phase II. Retention rates were about 63.9 percent in total but varied significantly across weekdays. Notably, subjects were less likely to return to the study on Friday.

Hence, in this pilot study, 36 subjects participated in phase I, and 23 in phase II. Their average reward was 32 dollars, with minimum and maximum ranging from 16 to 45. New rounds of invitations will be sent out over the next weeks until the final sample reaches about 100 subjects. While the number of invitations was equal across all service categories, acceptance and retention rates varied significantly, being highest in the music and audio, business, and data categories. The causes of the variation in engagement are unclear at this point, but seem unrelated to reward dominance, as categories with more expensive rates Table 10 are also the ones with higher representation in phases I and II (Table 13).

Table 12. Invitations, acceptances, and attrition rates by weekday

	Monday	Tuesday	Wednesday	Thursday	Friday	Total
Invitations sent	18	18	30	53	76	195
Phase I (acceptances)	5	6	3	10	12	36
Invitation acceptance (%)	27.8%	33.3%	10.0%	18.9%	15.8%	18.5%
Phase II (returnees)	3	6	2	8	4	23
Retention (%)	60.0%	100.0%	66.7%	80.0%	33.3%	63.9%

Table 13. Acceptances and Retention Rates by Category

	Phase I		Phase II	
Category	Total	Percent	Total	Retention
Music & Audio	9	25.0%	7	77.8%
Business	6	16.7%	4	66.7%
Lifestyle	6	16.7%	2	33.3%
Data	5	13.9%	5	100.0%
Writing & Translation	4	11.1%	3	75.0%
Programming & Tech	3	8.3%	1	33.3%
Digital Marketing	1	2.8%	1	100.0%
Graphics & Design	1	2.8%	0	0.0%
Video & Animation	1	2.8%	0	0.0%
Total	36	100.0%	23	63.9%

4.5 Results

4.5.1 Descriptive

This section provides a descriptive overview, considering data from the experimental and survey components of the study. Table 14 cross-tabulates the first measure of preference for flexibility (namely, deciding when to participate in phase II) with reliance on platform income. All participants said that platform earnings were either an important (75 percent) or very important (25 percent) earnings source to cover basic family expenses, and no one replied that it was slightly or moderately important. Based on these responses, the analysis in the current stage focuses on two levels of reliance. However, in future analyses, the investigation should be expanded to include all four levels of reliance. This broader analysis will provide a more comprehensive understanding of the relationship between preference for flexibility and reliance on platform income.

In phase I, no participant chose the very flexible option for slot selection (which would allow a roughly twelve hours window to participate). However, 42 percent of all respondents were willing to trade a $5 bonus for being able to pick their own slot – the somewhat flexible option. As expected from theory, preference for flexibility (choosing one's own slot) was higher among participants with higher income reliance.

Table 14. Preference for flexibility by Platform Reliance (Phase I)

	Importance of platform earnings to cover basic family expenses			
Flexibility level	Slightly important (0 to 24%)	Moderately important (25 to 49%)	Important (50 to 74%)	Very important (above 75%)
Get a random slot for $5 bonus (not flexible)	0.0%	0.0%	59.3%	55.6%
Choose own slot (somewhat flexible)	0.0%	0.0%	40.7%	44.4%
Any time in the day for a $5 cost (very flexible)	0.0%	0.0%	0.0%	0.0%
Total	0.0%	0.0%	100.0%	100.0%
N	0	0	27	9

Table 15 illustrates demographic characteristics of participants overall and by reliance on platform earnings. The sample is mainly comprised of white, highly educated, and married men. The demographic composition of the reliance groups differs, with the higher reliance group having higher proportions of women, white, high educated, and single individuals. On average, those with higher reliance were also younger, and less likely to be married or have children. Marital status and the presence of children serve as variables to capture potential additional income sources within the household and the presence of dependent children, respectively. It is well-documented that the presence of dependent children is associated with a higher preference for flexibility, especially for women.

More details about the use and perceptions of working in the platform are available in Table 16. Workers with higher reliance on platform income are more likely to be enrolled in additional platforms, but less likely to have a non-platform job. They also spend almost four times more hours doing platform work than those with lower reliance but work fewer hours on all jobs combined. Finally, most respondents have worked on platforms for more than a year and expect to continue to do it in the next year.

Table 15. Demographic Characteristics of Participants by Platform Reliance (Phase II)

	Reliance		Total
	Important (50 to 74%)	Very important (above 75%)	
Gender (%)			
Male	75.0	28.6	60.9
Female	25.0	57.1	34.8
Other	0.0	14.3	4.4
Race (%)			
White (non-Latino)	56.3	71.4	60.9
Black (non-Latino)	6.3	14.3	8.7
Asian (non-Latino)	6.3	14.3	8.7
Latino	18.8	0.0	13.0
None of the above	12.5	0.0	8.7
Educational attainment (%)			
Incomplete High School	0.0	14.3	4.4
High School Degree	12.5	14.3	13.0
Some College	25.0	0.0	17.4
Bachelor's degree	43.8	71.4	52.2
Graduate degree	18.8	0.0	13.0
Marital status (%)			
Married / living with	75.0	14.3	56.5
Never married	25.0	85.7	43.5
Children ages 0 to 15 in the household (%)	31.3	0.0	21.7
Mean age	35.3	31.3	34.1

When questioned about the main reason to have engaged in platform work, most participants indicated having a regular income supplement source or becoming their own bosses. Reasons highlighted in the moonlighting literature (job portfolios and constraints in the primary job) also showed up among choices for individuals with higher income reliance (Table 17).

Table 16. Use and Perceptions of Platforms by Platform Reliance (Phase II)

	Reliance		Total
	Important (50 to 74%)	Very important (above 75%)	
Work in other platforms (%)	43.8	57.1	47.8
Have a non-platform job (%)	87.5	42.9	73.9
Mean hours of work in platforms	6.2	24.0	11.6
Mean hours of work in all jobs	37.4	28.6	34.7
Time using platforms for work			
Less than a month	6.3	0.0	4.4
Between one and six months	6.3	0.0	4.4
Between six months and one year	25.0	14.3	21.7
More than one year	62.5	85.7	69.6
Expect to continue working in platforms in the next 12 months	87.5	85.7	87.0
N (phase II)	7	16	23

Table 17. Reasons to Use Platforms for Work Purposes (Phase II)

	Reliance		Total
Reason	Important (50 to 74%)	Very important (above 75%)	
To be my own boss	42.9	18.8	26.1
To work more hours than allowed in my other job	0.0	6.3	4.4
To supplement income on a regular basis	42.9	50.0	47.8
To supplement income on a temporary basis or for a specific purpose	14.3	12.5	13.0
To vary the type of task that I do for work	0.0	6.3	4.4
Other	0.0	6.3	4.4
Total	100.0	100.0	100.0

Participants were also asked open-ended questions about the main perceived advantages and disadvantages of working with Fiverr (Table 18). Advantages can be easily split into two categories: flexibility and business benefits. Mentions to flexibility referred to temporal and spatial schedule flexibility, choosing which projects to take, and autonomy in making decisions. Meanwhile, those who highlighted businesses benefits mentioned scale gains in terms of marketing and access to a large pool of clients.

Participants perceived disadvantages fit three main categories: platform rules, job precariousness, and competition. Platform rules – especially the Fiverr service fee – were the most cited disadvantage. Within job precariousness, uncertainty, which translates into earnings fluctuation, is the most common issue. Related to that, competition between sellers is seen as a disadvantage and an obstacle towards getting visibility on the platform. Interestingly, two respondents mention the growing number of spam messages as a disadvantage, which may explain the low response rates to the study invite.

4.5.2 Preferences for Flexibility

As discussed, preference for flexibility in this study was measured in various ways. Accordingly, in column 1 in Table 19, flexibility is the choice for the flexible participation slot in phase II, which costs subjects the bonus associated with getting a random slot. In columns 2-4, preference for flexibility consists of choosing the flexible option (contract B), which is an increasingly costlier alternative. Finally, in column 5, flexibility is represented as risk aversion, measured by switching to column B in the multiple price list task after row 5 – the natural switching point for a risk-neutral subject. Panel A plots coefficients obtained from bivariate regressions of preference for flexibility on income reliance (therefore, providing a difference of means test), and panel B adds demographic variables to the models.[30]

[30] In the MPL model, individuals who either switched from columns A and B multiple times (7), or who never switched across columns (2) were removed from the analysis, as these choices are inconsistent (Andersen et al. 2006; Jack, McDermott, and Sautmann 2022). Given the reduced number of remaining of observations in the pilot, a multivariate regression is not shown in Table 19.

Table 18. Greatest Advantages and Disadvantages of Working at Fiverr

Advantages	
Flexibility	"The ability to work from home." "I can do what I love make money in the comfort of my own home and something that's within my own profession." "I like that Fiverr gives me occasional additional work, but not too much; I already work a lot so I like the flexibility & freedom to choose when/if to take on more projects." "You control many major aspects of your work like wages, hours, and types of services." "I can be picky and choose fun projects to work on." "You are able to pick when you want to work and for how much." "Able to select my clients."
Business benefits	"Fiver has a recognized brand name in the gaming scene, and is reliable and fair viewing rates/algorithms." "Reduces risk of working with bad clients." "Fiverr does the majority of my marketing for me." "Fiverr does a lot of the advertising for me. In exchange for 20% of my income earned through the website, they show my service to roughly 2,000 or more people looking for my service every week." "To continue my passion on a global scale and earn more income." "It allows me to reach way more clients than I could've before." "One of the main advantages of using Fiverr is the opportunity to connect with many different potential clients and the ability to choose jobs."
Disadvantages	
Precariousness	"The lack of certainty when it comes to whether or not I'll receive consistent orders." "Waiting for clients to arrive." "It is a glorified sweat shop." "Work is not guaranteed, so income droughts can happen." "Sometimes clients want the most amount of work for the smallest price tier package."
Platform rules	"They take 20% of my earnings." "In a strange contradiction to my previous answer, the fact that they garnish 20% of my income is a bit of a curse for my work here. While I appreciate their advertising, I would be more inclined to lean heavier on the platform and get more work through them if they were to charge less for such a service. It's just advertising, not guaranteed work. I get more guaranteed jobs through auditions nowadays, but it's still helpful enough for me to keep them in my rotation." "Flooded market, 50% loss after taxes and Fiverr's cut of profits and tips." "The 20% cut that they take and the lack of steady work."
Competition	"The market can be very competitive." "Difficult to get visibility as a new seller." "There's a ton of competition for relatively low pay."
Other	"Scams, not enough work." "Sometimes there's a lot of spam accounts that snuck through the verification process."

At this pilot stage, the reduced number of observations in the sample prevents inferential analysis. However, it gives insights into the direction of relationships. Indeed, in the sample, participants with higher reliance on platform income had a higher preference for flexibility across all columns, and the introduction of demographic controls increased these differences. In columns 2-4, as the flexible option became more costly, the higher reliance group was even more likely to choose the flexible option as compared to the reference group. As the study advances and the sample size grows, it will provide a more robust basis for determining the generalizability of these findings to the broader population.

Table 19. Regressions on Preference for Flexibility

Variables	Flexible slot (part I) (1)	Chose B, round 1 (2)	Chose B, round 2 (3)	Chose B, round 3 (4)	Risk Aversion (5)
Panel A					
Higher reliance (more than 75%)	0.04	0.07	0.13	0.28	0.16
	(0.20)	(0.24)	(0.23)	(0.22)	(0.30)
Constant (50 to 74% reliance)	0.41***	0.50***	0.44***	0.44***	0.44**
	(0.10)	(0.13)	(0.13)	(0.13)	(0.18)
Demographics	No	No	No	No	No
Observations	36	23	23	23	14
R-squared	0.00	0.00	0.02	0.07	0.02
Panel B					
Higher reliance (more than 75%)	-0.25	0.19	0.27	0.63	
	(0.47)	(0.50)	(0.56)	(0.45)	
Constant (50 to 74% reliance)	0.39	3.05**	1.98*	-1.51	
	(1.29)	(0.99)	(1.05)	(0.92)	
Demographics	Yes	Yes	Yes	Yes	
Observations	23	23	23	23	
R-squared	0.70	0.72	0.66	0.72	

Note: Demographic variables included in panel B are gender, race, age, marital status, educational attainment, and the presence of children ages 0 to 15 in the household. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.6 Conclusion and Next Steps

Preference for flexibility has been claimed as one of the main reasons for engagement in platform work, but few studies have empirically assessed this claim, with exceptions in the ridesharing realm (K.-M. Chen et al. 2020; M. K. Chen et al. 2019). While freelance marketplaces within the platform economy are often portrayed as less precarious due to the increased autonomy they offer workers (Schmidt 2017), it is essential to empirically investigate whether individuals opt for this arrangement out of intrinsic preferences or other factors.

Based on the assumption that platform jobs are inherently less secure than standard jobs, it is anticipated that workers who rely on them as their primary source of income would exhibit a stronger preference for flexibility compared to those who rely on them to supplement their income. However, if this expectation does not align with the findings, it raises the possibility that platform workers may be motivated not by intrinsic preferences, but rather by external constraints such as unemployment or having jobs that do not make ends meet.

This essay proposed a mixed-method study to examine the preference for flexibility among workers in a prominent US freelance marketplace, contrasting workers by their income reliance. Although inferential conclusions cannot be drawn at this initial stage of data collection, the preliminary findings indicate that freelancers were indeed attracted to the Fiverr platform due to the desire for flexibility, and the majority anticipate continued platform usage in the near future. Within the sample, there is a positive association between income reliance and preference for flexibility across all three measures, and respondents also highlighted various forms of flexibility in their open-ended survey responses. These findings suggest that workers are inherently motivated by preferences for flexibility, which is a promising outcome. However, it is important to acknowledge that this does not imply freelance marketplaces are devoid of challenges. In fact, concerns regarding job availability and uncertainty surrounding the timing of jobs have emerged as notable issues within the context of this study.

As the data collection expands, the statistical robustness of the data analysis will strengthen. Additionally, the increased availability of data will provide an opportunity to examine variations in preference and perceptions among different groups of workers, including by gender and race.

Meanwhile, it is important to acknowledge certain limitations and consider strategies to mitigate them. First, accurately capturing the multifaceted concept of flexibility poses a challenge. To address this, a combination of observational and self-reported measures has been employed, recognizing that none of them is without flaws. However, together they provide a more comprehensive understanding and allow capturing the revealed preference.

Second, a potential concern is the presence of selection bias within the sample of respondents, as it may be skewed towards sellers who are more inclined to take risks (i.e., clicking on a link sent by a stranger). To address this issue, future endeavors aim to establish a partnership with Fiverr or integrate the research software within a university website, fostering increased trust and expanding the participant pool.

Third, the challenge of external validity is inherent in empirical studies. While the findings presented in this study may be specific to Fiverr and freelance marketplaces, in the future I will replicate this research in other crowd-work settings. By comparing crowd-work and freelance marketplaces, insights can be gained into how preferences versus necessity manifest in high-skill versus low-skill platform environments.

Chapter 5: Conclusions

This dissertation has examined platform work from various angles, contributing to the literature on ridesharing, occupational choice, and worker preferences. Collectively, the essays shed light on the outcomes and motivations of platform workers across different platforms and contexts, thereby enhancing the understanding of the challenges and opportunities associated with these expanding labor markets.

More specifically, the first essay discussed the impacts of ridesharing on drivers and job quality in Brazil, relying on the staggered entry of Uber in the country as a natural experiment opportunity. Here the main contribution lies precisely in expanding this literature to a large middle-income country and evaluating it in context. The results revealed an exponential increase in the number of self-employed drivers following Uber entry, accompanied by reductions in drivers' earnings, work hours, and subscriptions to social security. By the end of the period, drivers found themselves in a more vulnerable position compared to the pre-ridesharing era, while also exhibiting greater resemblance to other workers in the economy. These trends in job outcomes may be a result of both the shift in labor supply and the policies implemented by companies, with no evidence that they were caused by changes in the composition of drivers.

The second essay expanded the analysis of ridesharing in Brazil to investigate variations in gender responses. Theoretically, the flexibility inherent to ridesharing should disproportionately benefit women, who typically face higher labor force constraints. While the number of female drivers has significantly increased, the occupation remains dominated by men. However, female drivers have disproportionately benefited (or experienced fewer losses) than their male counterparts. Household composition and safety concerns emerge as important factors shaping women's decision to become drivers. For example, mothers of older children were more likely to drive after Uber, but mothers of young children were not. Further, structural barriers, such as violence, hinder women's involvement.

The last essay switches attention to platform workers in freelance marketplaces – online service labor markets operating globally. The contribution here lies in assessing the claim of a supposed preference for flexibility by comparing workers with different levels of dependence on platform earnings to meet their basic needs. Additionally, this essay proposes an innovative mixed-methods empirical strategy, combining an experiment and a survey. Preliminary results from a pilot identify a correlation between platform reliance and preference for flexibility, but more work is needed to clarify whether these findings are significant.

While this dissertation clarifies variations between and within the platform universe, its findings should not be understood in isolation but rather as part of a broader context of labor deregulation and increased insecurity. Indeed, the duality between flexibility and insecurity is not a novelty, but it tends to intensify as these platforms and other emerging technologies, including artificial intelligence, are increasingly incorporated into work life. In this context, the ability of existing regulations to effectively address the new challenges appears increasingly limited. Significant improvements in the quality of work will require innovative approaches to labor regulation, perhaps by attaching protections to the worker rather than specific jobs or employees.

Appendix A. Chapter 2 Supplementary Materials

Appendix A Tables

Table A1. Uber Rollout in Brazilian Capitals

Capital	Population 2010 (in thousands)	Region	Uber Entry
Rio de Janeiro (RJ)	11,836	Southeast	Q2-2014
São Paulo (SP)	19,684	Southeast	Q3-2014
Belo Horizonte (MG)	5,415	Southeast	Q3-2014
Brasília (DF)	3,718	Midwest	Q1-2015
Porto Alegre (RS)	3,959	South	Q4-2015
Goiânia (GO)	2,173	Midwest	Q1-2016
Recife (PE)	3,691	Northeast	Q1-2016
Curitiba (PR)	3,174	South	Q1-2016
Fortaleza (CE)	3,616	Northeast	Q2-2016
Salvador (BA)	3,574	Northeast	Q2-2016
Natal (RN)	1,351	Northeast	Q3-2016
João Pessoa (PB)	1,199	Northeast	Q3-2016
Vitória (ES)	1,688	Southeast	Q3-2016
Florianópolis (SC)	1,012	South	Q3-2016
Campo Grande (MS)*	787	Midwest	Q3-2016
Maceió (AL)	1,156	Northeast	Q4-2016
Teresina (PI)	1,151	Northeast	Q4-2016
Cuiabá (MT)	834	Midwest	Q4-2016
Aracaju (SE)	836	Northeast	Q4-2016
Belém (PA)	2,102	North	Q1-2017
São Luís (MA)	1,331	Northeast	Q1-2017
Palmas (TO)*	228	North	Q1-2017
Manaus (AM)	2,106	North	Q2-2017
Porto Velho (RO)*	429	North	Q2-2017
Rio Branco (AC)*	336	North	Q2-2017
Boa Vista (RR)*	284	North	Q2-2017
Macapá (AP)	499	North	Q3-2017

Note: 1. Most Brazilian capitals fall within a metropolitan region. The asterisk indicates those that are not, in which case the population refers to each city's.
Source: IBGE. Sinopse do Censo Demográfico 2010, Table 3.2.

Table A2. Summary Statistics (Sample of Workers, Pooled Years)

Variables	Mean	Std. Dev.
Usual monthly earnings	2,229.27	2,270.90
Hourly earnings	13.00	14.69
Usual weekly hours worked	40.30	10.81
Social security contributor	0.69	0.46
SE driver	0.01	0.11
Other driver	0.01	0.11
Informal worker	0.16	0.37
Formal worker	0.56	0.50
Other SE	0.25	0.43
Men	0.54	0.50
Women	0.46	0.50
Not married (no partner present)	0.43	0.49
Married (partner present)	0.57	0.49
White	0.44	0.50
Black	0.56	0.50
Less than Elementary School	0.22	0.41
Elementary School / Incomplete High School	0.16	0.36
High School / Incomplete College	0.43	0.50
College or Higher	0.19	0.39
Age	39.75	12.02
N (unweighted)		2,156,286

Table A3. Logistic Regression on Self-Employed Driver (years 2012-2013 vs 2018-2019)

Variables	All drivers (1)	Not self-employed drivers (2)	Self-employed drivers (3)	(4)
Uber	0.24***	-0.16***	0.60***	1.16***
	(0.02)	(0.03)	(0.03)	(0.16)
Female	-2.72***	-3.55***	-2.39***	-2.32***
	(0.08)	(0.15)	(0.07)	(0.09)
Black	-0.16***	-0.02	-0.25***	-0.29***
	(0.04)	(0.02)	(0.05)	(0.06)
Married	0.13***	0.44***	0.10***	0.22***
	(0.01)	(0.04)	(0.03)	(0.03)
Age	0.03***	-0.00**	0.04***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)
Elementary	0.56***	0.58***	0.58***	0.49***
	(0.02)	(0.03)	(0.04)	(0.04)
High School	0.70***	0.55***	0.88***	0.57***
	(0.07)	(0.08)	(0.07)	(0.05)
College or higher	-0.70***	-1.33***	-0.20**	-0.76***
	(0.14)	(0.26)	(0.08)	(0.13)
Uber * Female				-0.09
				(0.08)
Uber * Black				0.05
				(0.04)
Uber * Married				-0.16***
				(0.06)
Uber * Age				-0.02***
				(0.00)
Uber * Elementary				0.17***
				(0.05)
Uber * High School				0.48***
				(0.05)
Uber * College or higher				0.78***
				(0.08)
Constant	-4.69***	-4.63***	-6.01***	-6.46***
	(0.05)	(0.04)	(0.05)	(0.12)
Observations	2,156,286	3,591,311	2,156,286	2,156,286
Pseudo R-squared	0.122	0.134	0.115	0.117

Note: All models control for metropolitan and quarter fixed effects. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4. Parallel Trends: Self-Employed Drivers vs Formal Workers

Variables	(1) Log. Monthly Earnings	(2) Log. Hourly Earnings	(3) Weekly Hours Worked
SE Driver	455.52***	0.64**	6.61***
	(57.47)	(0.28)	(1.07)
2012q2	31.49	0.12	-0.09*
	(37.90)	(0.24)	(0.05)
2012q3	1.15	-0.03	-0.13**
	(28.77)	(0.12)	(0.05)
2012q4	3.40	0.10	-0.25***
	(33.05)	(0.22)	(0.07)
2013q1	4.65	0.07	-0.27***
	(19.85)	(0.15)	(0.07)
2013q2	43.94	0.29	-0.36***
	(37.58)	(0.28)	(0.07)
2013q3	91.49***	0.56**	-0.39***
	(25.00)	(0.23)	(0.11)
2013q4	65.33***	0.39***	-0.52***
	(18.82)	(0.13)	(0.11)
2014q1	108.65***	0.60***	-0.52***
	(35.85)	(0.21)	(0.12)
2012q2 * SE Driver	39.23	0.07	-0.04
	(54.68)	(0.66)	(1.64)
2012q3 * SE Driver	78.22	1.00	-1.07
	(71.94)	(0.82)	(0.97)
2012q4 * SE Driver	250.94	1.26**	-0.06
	(156.73)	(0.60)	(1.51)
2013q1 * SE Driver	5.08	0.29	-0.91
	(70.37)	(0.51)	(1.12)
2013q2 * SE Driver	122.46	1.84**	-1.28
	(82.39)	(0.68)	(1.20)
2013q3 * SE Driver	172.30**	0.86*	-0.69
	(83.47)	(0.48)	(1.15)
2013q4 * SE Driver	202.53***	1.79***	-0.37
	(69.14)	(0.27)	(0.79)
2014q1 * SE Driver	46.34	0.49*	-1.17
	(79.10)	(0.27)	(0.86)
Constant	1,938.40***	10.10***	44.23***
	(24.27)	(0.17)	(0.07)
Observations	347,834	347,834	347,834
R-squared	0.03	0.02	0.01

Note: Formal worker is the reference group. All models include metropolitan fixed effects. The R-squared reported in columns 4 is a Pseudo R-squared. Interactions between year-quarter and self-employed driver test the parallel trends assumption. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5. Parallel Trends: Self-Employed Drivers vs Informal Workers

Variables	(1) Log. Monthly Earnings	(2) Log. Hourly Earnings	(3) Weekly Hours Worked	(4) Social security (logit model)
SE Driver	848.34***	1.05***	11.90***	1.10***
	(83.81)	(0.27)	(1.48)	(0.10)
2012q2	-84.74*	-0.45*	-0.40**	-0.08
	(41.29)	(0.25)	(0.16)	(0.06)
2012q3	-65.38**	-0.12	-0.66**	0.02
	(31.27)	(0.16)	(0.26)	(0.05)
2012q4	-108.64**	-0.59**	-0.63***	-0.02
	(45.30)	(0.28)	(0.22)	(0.08)
2013q1	-16.93	0.11	-0.96***	0.11**
	(33.21)	(0.21)	(0.19)	(0.04)
2013q2	-19.88	0.28	-1.25***	0.10
	(49.14)	(0.22)	(0.24)	(0.07)
2013q3	28.58	0.38	-1.39***	0.13*
	(60.81)	(0.28)	(0.34)	(0.08)
2013q4	27.59	0.48	-1.20***	0.15
	(62.45)	(0.29)	(0.24)	(0.09)
2014q1	46.85*	0.55**	-1.33***	0.19***
	(25.71)	(0.21)	(0.37)	(0.07)
2012q2 * SE Driver	160.85**	0.66*	0.30	-0.10
	(70.29)	(0.33)	(1.68)	(0.15)
2012q3 * SE Driver	145.70**	1.09	-0.53	-0.13
	(62.01)	(0.76)	(1.12)	(0.16)
2012q4 * SE Driver	371.18***	1.97***	0.39	-0.08
	(131.82)	(0.46)	(1.49)	(0.15)
2013q1 * SE Driver	28.82	0.27	-0.31	-0.25***
	(101.91)	(0.66)	(1.13)	(0.09)
2013q2 * SE Driver	192.07**	1.87***	-0.39	0.07
	(77.72)	(0.64)	(1.24)	(0.12)
2013q3 * SE Driver	226.79**	1.00**	0.24	-0.09
	(106.04)	(0.44)	(1.30)	(0.10)
2013q4 * SE Driver	234.42**	1.68***	0.20	0.03
	(92.08)	(0.39)	(0.78)	(0.09)
2014q1 * SE Driver	108.30	0.54**	-0.37	-0.17*
	(114.03)	(0.24)	(1.16)	(0.09)
Constant	1,775.98***	10.49***	39.97***	-1.71***
	(36.00)	(0.14)	(0.24)	(0.05)
Observations	109,721	109,721	109,721	109,721
R-squared	0.04	0.02	0.05	0.03

Note: Informal worker is the reference group. All models include metropolitan fixed effects. The R-squared reported in columns 4 is a Pseudo R-squared. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A6. Parallel Trends: Self-Employed Drivers vs Other Self-Employed

Variables	(1) Log. Monthly Earnings	(2) Log. Hourly Earnings	(3) Weekly Hours Worked	(4) Social security (logit model)
SE Driver	628.73***	-0.26	10.37***	0.92***
	(38.11)	(0.38)	(1.52)	(0.09)
2012q2	-33.53	-0.22	-0.11	-0.08*
	(22.19)	(0.14)	(0.14)	(0.04)
2012q3	4.72	0.07	-0.05	0.02
	(37.47)	(0.30)	(0.19)	(0.05)
2012q4	58.08	0.11	0.05	-0.01
	(84.31)	(0.54)	(0.19)	(0.04)
2013q1	48.96	0.62	-0.19	0.09***
	(42.61)	(0.53)	(0.30)	(0.03)
2013q2	82.04*	0.61**	-0.12	0.14***
	(44.01)	(0.28)	(0.22)	(0.05)
2013q3	127.15***	0.42	0.16	0.15**
	(45.57)	(0.29)	(0.20)	(0.07)
2013q4	101.87***	0.61**	0.12	0.13*
	(21.72)	(0.24)	(0.28)	(0.07)
2014q1	212.86***	1.08**	0.33	0.22***
	(44.51)	(0.40)	(0.31)	(0.07)
2012q2 * SE Driver	103.57*	0.40	-0.01	-0.11
	(59.45)	(0.50)	(1.64)	(0.13)
2012q3 * SE Driver	70.41	0.88	-1.19	-0.13
	(66.29)	(0.83)	(0.95)	(0.14)
2012q4 * SE Driver	205.37	1.26	-0.23	-0.08
	(173.52)	(0.86)	(1.48)	(0.15)
2013q1 * SE Driver	-61.68	-0.37	-1.18	-0.28***
	(48.29)	(0.48)	(1.40)	(0.10)
2013q2 * SE Driver	73.75	1.43*	-1.52	0.02
	(84.57)	(0.74)	(1.34)	(0.11)
2013q3 * SE Driver	120.32	0.91*	-1.37	-0.12
	(80.49)	(0.46)	(1.36)	(0.10)
2013q4 * SE Driver	149.70**	1.49***	-1.13	0.03
	(71.29)	(0.26)	(0.93)	(0.11)
2014q1 * SE Driver	-74.87	-0.09	-2.07*	-0.22*
	(84.94)	(0.32)	(1.02)	(0.12)
Constant	1,881.69***	11.09***	41.17***	-1.68***
	(30.53)	(0.27)	(0.16)	(0.04)
Observations	155,625	155,625	155,625	155,625
R-squared	0.05	0.02	0.03	0.04

Note: Other self-employed is the reference group. All models include metropolitan fixed effects. The R-squared reported in columns 4 is a Pseudo R-squared. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7. Parallel Trends: Self-Employed Drivers vs Other Drivers

Variables	Log. Monthly Earnings (1)	Log. Hourly Earnings (2)	Weekly Hours Worked (3)	Social security (logit model) (4)
SE Driver	827.86***	3.36***	4.26***	-1.84***
	(116.14)	(0.77)	(1.35)	(0.08)
2012q2	-13.02	-0.18	0.45	-0.04
	(49.96)	(0.32)	(0.57)	(0.12)
2012q3	13.74	0.18	0.03	-0.11
	(66.15)	(0.28)	(0.64)	(0.13)
2012q4	78.11	0.28	0.31	-0.34*
	(52.49)	(0.25)	(0.52)	(0.19)
2013q1	24.13	0.42	-0.37	-0.09
	(62.71)	(0.34)	(0.60)	(0.15)
2013q2	46.74	0.26	0.02	-0.33
	(45.95)	(0.25)	(0.44)	(0.23)
2013q3	111.16	0.86	-0.25	-0.05
	(85.80)	(0.51)	(0.40)	(0.19)
2013q4	67.44	0.64	-0.73*	0.02
	(84.17)	(0.42)	(0.37)	(0.22)
2014q1	35.07	0.32	-0.95	0.30*
	(74.31)	(0.35)	(0.77)	(0.16)
2012q2 * SE Driver	66.14	0.32	-0.69	-0.15
	(77.91)	(0.60)	(1.87)	(0.20)
2012q3 * SE Driver	56.50	0.79	-1.35	-0.01
	(88.77)	(0.73)	(1.50)	(0.16)
2012q4 * SE Driver	161.43	1.00*	-0.63	0.24
	(161.42)	(0.55)	(1.75)	(0.24)
2013q1 * SE Driver	-31.28	-0.05	-1.03	-0.09
	(69.43)	(0.52)	(1.43)	(0.19)
2013q2 * SE Driver	91.69	1.80**	-1.84	0.48*
	(94.33)	(0.77)	(1.41)	(0.28)
2013q3 * SE Driver	141.14	0.55	-0.92	0.06
	(129.14)	(0.72)	(1.23)	(0.21)
2013q4 * SE Driver	191.83*	1.53***	-0.25	0.14
	(109.41)	(0.49)	(0.94)	(0.21)
2014q1 * SE Driver	92.62	0.70**	-0.92	-0.31*
	(111.85)	(0.33)	(1.47)	(0.18)
Constant	1,767.53***	7.93***	48.28***	1.46***
	(75.01)	(0.43)	(0.54)	(0.11)
Observations	13,345	13,345	13,345	13,345
R-squared	0.13	0.08	0.03	0.15

Note: Other Driver is the reference group. All models include metropolitan fixed effects. The R-squared reported in columns 4 is a Pseudo R-squared. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A8. Income Models with and without Informal Workers in the Control Group

Variables	Log. Monthly Earnings (1)	(2)	Log. Hourly Earnings (3)	(4)
Uber	-0.20***	-0.20***	-0.15***	-0.15***
	(0.02)	(0.02)	(0.03)	(0.03)
Other driver	-0.19***	-0.19***	-0.14***	-0.14***
	(0.03)	(0.03)	(0.03)	(0.03)
Informal worker	-0.29***		-0.06**	
	(0.02)		(0.02)	
Formal worker	-0.14***	-0.14***	-0.11***	-0.11***
	(0.03)	(0.03)	(0.02)	(0.02)
Other self-employed	-0.33***	-0.33***	-0.13***	-0.13***
	(0.02)	(0.02)	(0.02)	(0.02)
Uber * Other driver	0.13***	0.13***	0.11***	0.11***
	(0.02)	(0.02)	(0.03)	(0.03)
Uber * Informal worker	0.13***		0.11***	
	(0.01)		(0.02)	
Uber * Formal worker	0.17***	0.17***	0.13***	0.13***
	(0.02)	(0.02)	(0.03)	(0.03)
Uber * Other self-employed	0.08***	0.08***	0.07**	0.07**
	(0.02)	(0.02)	(0.03)	(0.03)
Constant	7.17***	7.17***	1.80***	1.80***
	(0.03)	(0.03)	(0.02)	(0.02)
Observations	2,156,286	1,779,543	2,156,286	1,779,543
R-squared	0.41	0.41	0.39	0.40

Note: All models include demographic controls, and quarter and metropolitan fixed effects. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A9. Log-likelihoods of working as self-employed drivers in t given job status in t-1

Variables	Self-Employed Driver (1)	Log. Monthly Earnings (2)	Log. Hourly Earnings (3)	Weekly Hours Worked (4)	Social security (logit) (5)
Uber	-0.38***	-0.07***	-0.07***	-0.17	-0.05***
	(0.01)	(0.02)	(0.03)	(0.64)	(0.01)
Other driver (t-1)	-0.57***				
	(0.02)				
Informal worker (t-1)	-0.00				
	(0.03)				
Formal worker (t-1)	0.36***				
	(0.02)				
Other self-employed (t-1)	0.55***				
	(0.02)				
Unemployed (t-1)	-0.98***				
	(0.05)				
Not in labor force (t-1)	1.00***				
	(0.02)				
Uber * Other driver (t-1)	1.62***				
	(0.02)				
Uber * Informal worker (t-1)	0.60***				
	(0.03)				
Uber * Formal worker (t-1)	0.13***				
	(0.02)				
Uber * Other self-employed (t-1)	0.71***				
	(0.02)				
Uber * Unemployed (t-1)	2.36***				
	(0.05)				
Uber * Not in labor force (t-1)	-0.09***				
	(0.03)				
Constant		7.62***	2.36***	45.87***	
		(0.01)	(0.02)	(0.40)	
Observations	1,639	2,863	2,863	2,863	1,442
Number of individuals	444	713	713	713	334

Note: The sample includes individuals who showed up between 3 and 5 times in the panel during a period in which Uber entered their cities, who had at least one pre- and one post-Uber entry period available in the data, and who were worked as self-employed driver in at least one but not all periods. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix A Figures

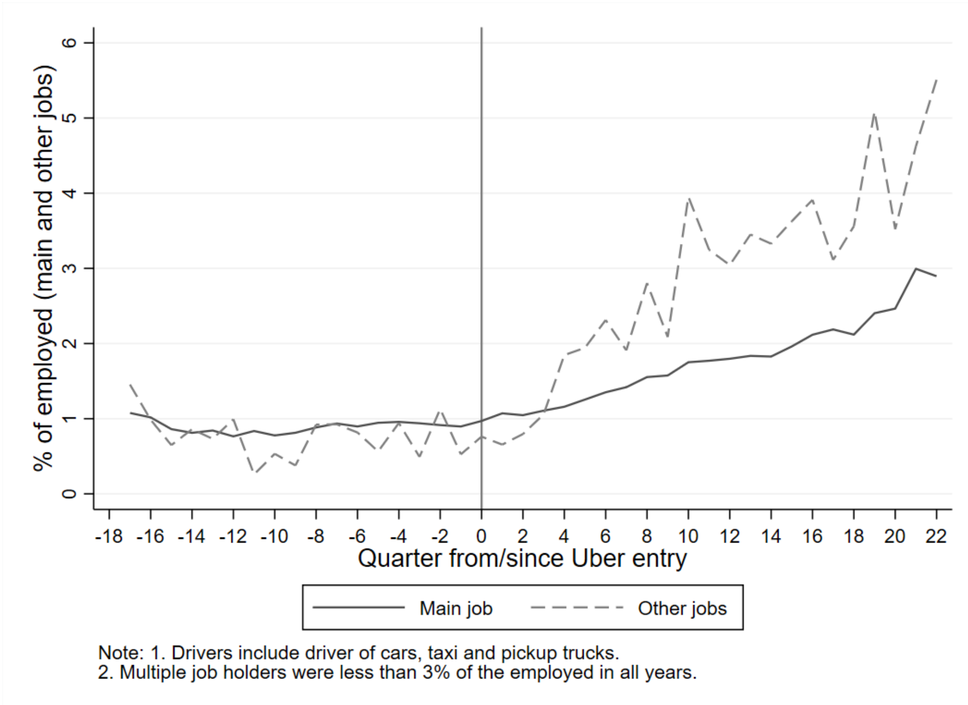


Figure A1. Proportion of Drivers in Primary and Secondary Jobs in Brazilian capitals

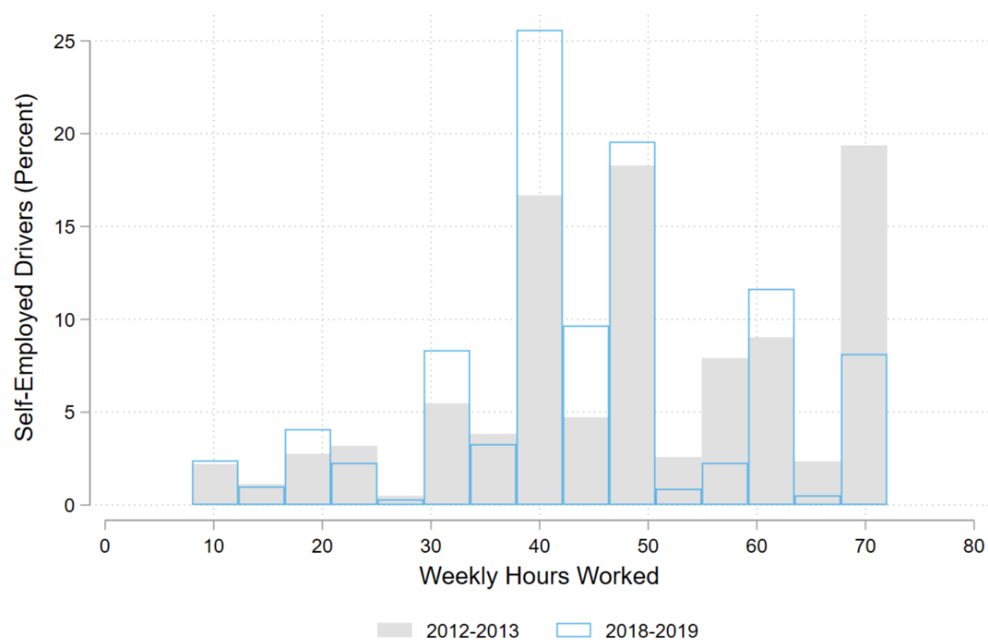


Figure A2. Distribution of Weekly Hours Worked of Self-Employed Drivers

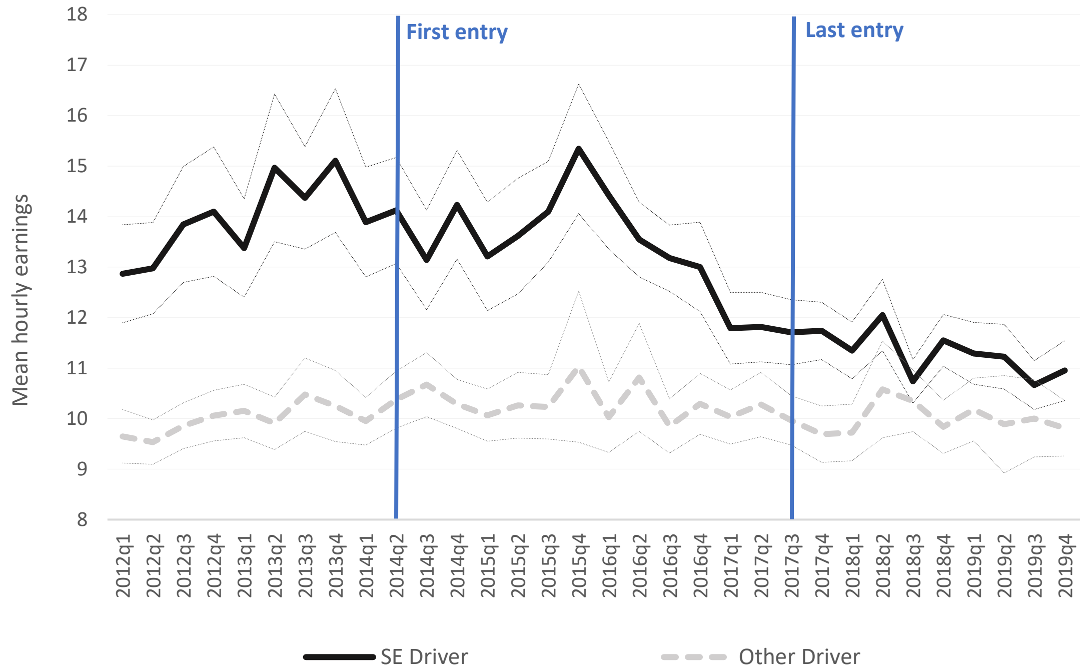


Figure A3. Changes in Hourly Wages of Self-Employed Drivers and Other Drivers

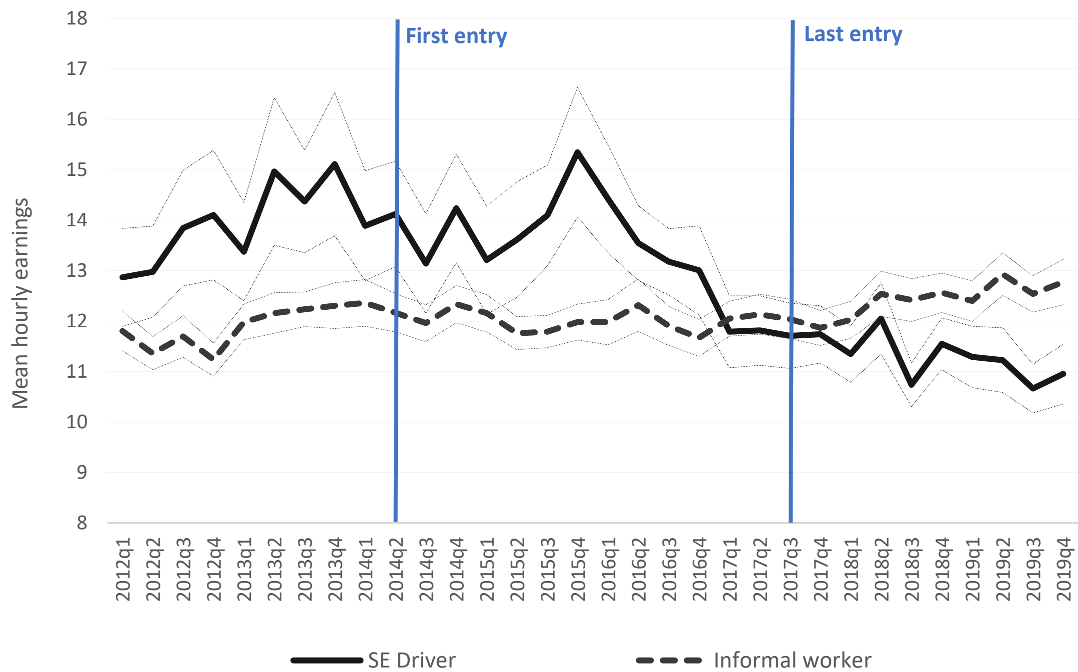


Figure A4. Changes in Hourly Wages of Self-Employed Drivers and Informal Workers

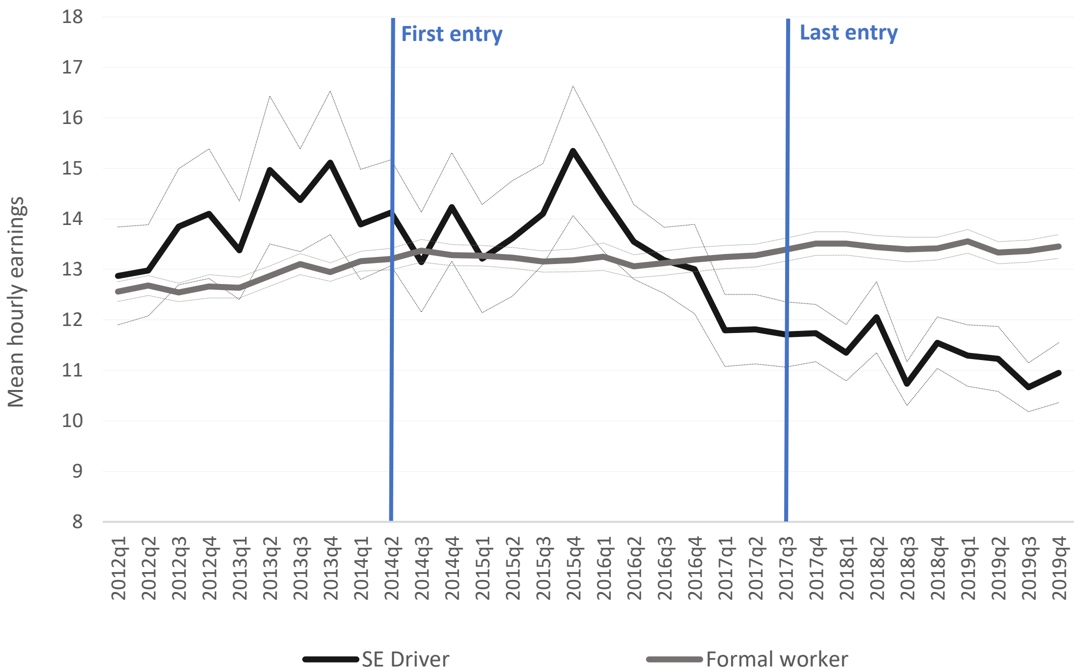


Figure A5. Changes in Hourly Wages of Self-Employed Drivers and Formal Workers

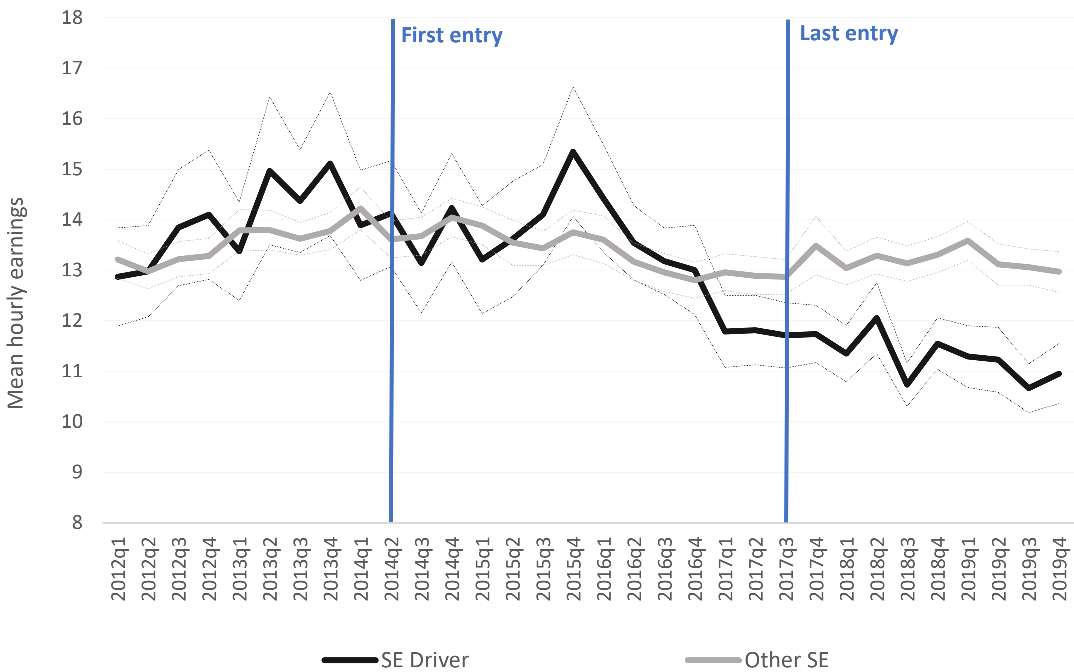


Figure A6. Changes in Hourly Wages of Self-Employed Drivers and Other Self-Employed

Appendix B. Chapter 3 Supplementary Materials

Appendix B Tables

Table B1. Self-employed Drivers in Brazilian Capitals

Period	Female	Male	Total
2012q1	23,842	246,248	270,090
2012q2	18,663	235,936	254,599
2012q3	24,780	228,327	253,108
2012q4	15,325	228,472	243,797
2013q1	21,232	233,169	254,401
2013q2	18,716	223,406	242,122
2013q3	17,596	218,975	236,571
2013q4	10,950	227,988	238,938
2014q1	15,964	210,831	226,795
2014q2	19,437	246,142	265,579
2014q3	13,449	262,453	275,902
2014q4	22,228	260,345	282,573
2015q1	23,562	248,246	271,808
2015q2	22,357	263,062	285,419
2015q3	21,086	258,702	279,789
2015q4	23,535	280,837	304,372
2016q1	29,416	308,975	338,391
2016q2	27,102	320,475	347,577
2016q3	26,383	338,125	364,508
2016q4	22,604	361,295	383,898
2017q1	24,215	364,347	388,562
2017q2	29,974	408,495	438,468
2017q3	33,035	410,501	443,536
2017q4	35,264	427,599	462,863
2018q1	33,914	473,068	506,982
2018q2	32,207	520,575	552,782
2018q3	34,414	514,453	548,867
2018q4	41,756	542,235	583,991
2019q1	48,517	607,814	656,331
2019q2	45,938	640,607	686,544
2019q3	54,006	694,748	748,754
2019q4	48,681	677,003	725,684

Table B2. Transportation Fatalities and Female Homicide Rates in Brazil (2011-2018)

	Transportation Fatalities Rates		Female Homicide Rates	
Capital (State)	Mean	Std. Dev	Mean	Std. Dev
Aracaju (SE)	12.5	9.2	4.5	1.1
Belo Horizonte (MG)	11.3	7.0	4.2	1.9
Belém (PA)	7.0	6.8	8.2	1.5
Boa Vista (RR)	27.7	6.0	6.5	2.8
Brasília (DF)	16.8	3.6	4.4	1.0
Campo Grande (MS)	22.1	4.2	3.8	1.0
Cuiabá (MT)	25.8	3.5	5.5	2.4
Curitiba (PR)	11.3	6.7	4.4	1.2
Florianópolis (SC)	15.7	3.4	2.7	0.4
Fortaleza (CE)	14.0	5.9	8.2	2.8
Goiânia (GO)	22.2	5.3	7.2	1.6
João Pessoa (PB)	15.3	1.5	8.0	2.4
Macapá (AP)	16.1	7.0	4.7	1.5
Maceió (AL)	13.1	7.8	7.7	2.1
Manaus (AM)	15.0	2.5	6.6	0.7
Natal (RN)	1.0	0.1	6.3	1.9
Palmas (TO)	28.2	2.9	5.6	1.7
Porto Alegre (RS)	5.2	6.3	6.4	1.8
Porto Velho (RO)	27.8	10.1	7.5	1.2
Recife (PE)	6.6	6.4	4.9	1.1
Rio Branco (AC)	16.1	6.3	6.8	2.5
Rio de Janeiro (RJ)	6.9	7.3	3.5	0.4
Salvador (BA)	1.7	4.0	6.8	1.2
São Luís (MA)	11.3	6.6	4.7	1.2
São Paulo (SP)	4.8	6.5	1.9	0.7
Teresina (PI)	25.6	2.2	4.0	1.2
Vitória (ES)	9.0	6.7	6.1	2.7

Note: Rates per 100 thousand population.

Table B3. Logit Regressions on Self-Employed Driver

Variables	(1) All	(2) Male	(3) Female
Uber	0.60***	1.14***	0.32
	(0.03)	(0.16)	(0.53)
Female	-2.38***		
	(0.09)		
Uber * Female	-0.02		
	(0.08)		
Black	-0.25***	-0.28***	-0.44***
	(0.05)	(0.07)	(0.15)
Married	0.11***	0.23***	0.25**
	(0.03)	(0.03)	(0.12)
Age	0.04***	0.05***	0.05***
	(0.00)	(0.00)	(0.01)
Elementary School	0.58***	0.50***	0.29*
	(0.04)	(0.04)	(0.17)
High School	0.88***	0.54***	0.94***
	(0.07)	(0.05)	(0.16)
College or higher	-0.20**	-0.82***	-0.09
	(0.08)	(0.15)	(0.41)
Children ages 0 to 6 in the household	0.01	-0.09	-0.14
	(0.02)	(0.09)	(0.30)
Children ages 7 to 15 in the household	-0.02	-0.07	0.09
	(0.02)	(0.08)	(0.09)
Children (0 to 6) * Children (7 to 15)		0.17	0.48
		(0.14)	(0.29)
Uber * Black		0.04	0.22
		(0.04)	(0.14)
Uber * Married		-0.20***	-0.11
		(0.04)	(0.16)
Uber * Age		-0.02***	-0.02*
		(0.00)	(0.01)
Uber * Elementary School		0.15***	0.63*
		(0.04)	(0.35)
Uber * High School		0.46***	0.97***
		(0.05)	(0.24)
Uber * College or higher		0.76***	1.26***
		(0.10)	(0.45)
Uber * Children (0 to 6)		0.23**	-0.65***
		(0.12)	(0.24)
Uber * Children (7 to 15)		0.10	-0.08
		(0.13)	(0.20)
Uber * Children (0 to 6) * Children (7 to 15)		-0.41*	0.20
		(0.21)	(0.22)

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Table B4. Logit Regressions on Self-Employed Driver (continued)

Variables	(1) All	(2) Male	(3) Female
Constant	-6.00***	-6.45***	-8.67***
	(0.05)	(0.12)	(0.39)
Observations	2,156,286	1,179,023	977,263
Pseudo R-squared	0.12	0.05	0.05

Note: All models control for metropolitan and quarter fixed effects. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B5. Linear Regressions on Job Outcomes: Interactions with Driver Demographics

Variables	Women			Men		
	Log. Monthly Earnings (1)	Log. Hourly Earnings (2)	Weekly Hours Worked (3)	Log. Monthly Earnings (4)	Log. Hourly Earnings (5)	Weekly Hours Worked (6)
Uber	-0.83**	-0.69*	-7.65	-0.29***	-0.18***	-6.32***
	(0.35)	(0.37)	(5.36)	(0.07)	(0.05)	(1.58)
Black	-0.06	-0.12	2.87	-0.13**	-0.12**	-0.46
	(0.05)	(0.09)	(1.91)	(0.05)	(0.05)	(0.35)
Married	0.12*	0.12*	-1.00	0.06*	0.03	1.08
	(0.06)	(0.06)	(1.86)	(0.03)	(0.04)	(0.81)
Age	-0.01*	-0.01	-0.15**	0.00**	0.00***	-0.04
	(0.01)	(0.01)	(0.06)	(0.00)	(0.00)	(0.03)
Elementary School	0.41***	0.34***	0.59	0.19***	0.14***	1.07
	(0.12)	(0.09)	(2.54)	(0.03)	(0.03)	(0.75)
High School	0.67***	0.69***	-1.58	0.28***	0.24***	0.91
	(0.13)	(0.11)	(2.66)	(0.03)	(0.02)	(1.08)
College or higher	1.22***	1.26***	-2.73	0.52***	0.48***	0.49
	(0.20)	(0.21)	(2.46)	(0.06)	(0.05)	(1.73)
Children ages 0 to 6	-0.16	-0.00	-5.31**	0.04	-0.02	2.58**
	(0.12)	(0.11)	(2.17)	(0.04)	(0.03)	(1.07)
Children ages 7 to 15	-0.11	0.00	-4.08*	0.03	0.02	0.11
	(0.08)	(0.09)	(2.18)	(0.03)	(0.02)	(0.57)
Children 0 to 6 & 7 to 15	0.03	-0.15	6.50*	-0.04	-0.04	0.29
	(0.17)	(0.16)	(3.39)	(0.08)	(0.07)	(1.34)
Uber * Black	0.07	0.13	-2.27	0.07	0.07	0.13
	(0.06)	(0.10)	(1.94)	(0.05)	(0.05)	(0.45)
Uber * Married	-0.07	0.03	-3.32*	0.04	0.02	0.82
	(0.12)	(0.11)	(1.91)	(0.06)	(0.05)	(0.77)
Uber * Age	0.02***	0.02**	0.07	0.00	0.00	0.02
	(0.01)	(0.01)	(0.06)	(0.00)	(0.00)	(0.02)
Uber * Elementary School	-0.07	-0.16	4.65	-0.04	-0.06**	1.35*
	(0.18)	(0.16)	(3.28)	(0.03)	(0.03)	(0.79)
Uber * High School	-0.11	-0.31**	7.67*	-0.00	-0.05*	2.15*
	(0.17)	(0.12)	(4.05)	(0.04)	(0.03)	(1.25)
Uber * College or higher	-0.62**	-0.86***	8.58***	-0.08	-0.11*	1.98
	(0.28)	(0.25)	(2.82)	(0.08)	(0.06)	(2.26)

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Table B5 (continued)

	Women			Men		
Variables	Log. Monthly Earnings (1)	Log. Hourly Earnings (2)	Weekly Hours Worked (3)	Log. Monthly Earnings (4)	Log. Hourly Earnings (5)	Weekly Hours Worked (6)
Uber * Children 0 to 6)	0.24**	0.18	1.92	0.01	0.03	-0.60
	(0.11)	(0.11)	(2.55)	(0.06)	(0.07)	(1.45)
Uber * Children 7 to 15	0.19**	0.16	1.71	0.00	-0.01	0.70
	(0.08)	(0.14)	(2.83)	(0.03)	(0.03)	(0.66)
Uber * Children 0-6 & 7-15	-0.25	0.08	-9.57	-0.04	-0.02	-1.58
	(0.16)	(0.22)	(6.62)	(0.10)	(0.12)	(2.03)
Constant	7.03***	1.61***	50.07***	7.44***	2.13***	47.85***
	(0.29)	(0.32)	(4.66)	(0.06)	(0.05)	(1.50)
Observations	1,803	1,803	1,803	25,837	25,837	25,837
R-squared	0.19	0.19	0.11	0.16	0.12	0.04

Note: All models control for metropolitan and quarter fixed effects. Linear predictions portrayed in Figure 5 and Figure B5 to Figure B7 (Appendix B). Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B6. Parallel Trends: Gender Differences Prior to Uber Entry

	All workers		SE Drivers only		
	Self-Employed Driver	In Labor Force	Log. Monthly Earnings	Log. Hourly Earnings	Weekly Hours Worked
Variables	(1)	(2)	(3)	(4)	(5)
Female	-2.13***	-1.16***	-0.55***	-0.26	-12.75***
	(0.15)	(0.03)	(0.12)	(0.17)	(1.79)
2012q2	-0.06	0.03**	-0.02	-0.01	-0.69
	(0.05)	(0.02)	(0.02)	(0.04)	(1.44)
2012q3	-0.09*	0.02	0.01	0.04	-1.18
	(0.05)	(0.02)	(0.02)	(0.05)	(1.06)
2012q4	-0.09	0.03*	0.03	0.03	-0.40
	(0.07)	(0.02)	(0.04)	(0.05)	(1.50)
2013q1	-0.05	0.02*	-0.00	0.02	-1.67
	(0.05)	(0.01)	(0.03)	(0.03)	(1.39)
2013q2	-0.13	0.05	0.02	0.07**	-2.37**
	(0.09)	(0.03)	(0.03)	(0.03)	(1.02)
2013q3	-0.16***	0.03	0.05	0.07**	-1.66
	(0.05)	(0.02)	(0.03)	(0.03)	(1.27)
2013q4	-0.12**	0.01	0.05**	0.10***	-1.79*
	(0.05)	(0.03)	(0.02)	(0.02)	(0.90)
2014q1	-0.18**	0.00	-0.00	0.04**	-2.34**
	(0.09)	(0.03)	(0.03)	(0.02)	(1.03)
2012q2 * Female	-0.22	-0.00	0.24**	0.24*	2.43
	(0.25)	(0.01)	(0.10)	(0.13)	(2.36)
2012q3 * Female	0.10	0.01	-0.11	-0.03	-0.91
	(0.12)	(0.01)	(0.14)	(0.16)	(2.04)
2012q4 * Female	-0.39**	0.00	0.15	0.36	-4.61
	(0.18)	(0.02)	(0.17)	(0.26)	(3.90)
2013q1 * Female	-0.07	0.02	0.08	0.11	0.13
	(0.30)	(0.02)	(0.15)	(0.26)	(4.25)
2013q2 * Female	-0.15	-0.01	0.28***	0.27**	3.18
	(0.21)	(0.03)	(0.09)	(0.12)	(2.11)
2013q3 * Female	-0.20	0.03	0.51**	0.46**	2.49
	(0.22)	(0.02)	(0.21)	(0.22)	(2.28)
2013q4 * Female	-0.72***	0.03	0.51***	0.46*	3.27
	(0.26)	(0.02)	(0.18)	(0.25)	(5.17)
2014q1 * Female	-0.27	0.04**	0.60***	0.57*	1.77
	(0.18)	(0.02)	(0.21)	(0.28)	(2.76)
Constant	-4.07***	1.32***	7.68***	2.13***	57.97***
	(0.05)	(0.02)	(0.01)	(0.02)	(0.97)
Observations	610,454	987,722	5,357	5,357	5,357
R-squared	0.07	0.05	0.14	0.11	0.07

Note: Male is the reference group. All models include metropolitan fixed effects. The R-squared reported in columns 1 and 2 are Pseudo R-squared. Interactions between year-quarter and gender test the parallel trends assumption. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B7. Self-Employed Driver Logit Models: Canonical versus Staggered Difference-in-Differences

	All		Women		Men	
	Canonical	Staggered	Canonical	Staggered	Canonical	Staggered
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Uber	0.60***	0.88***	0.32	1.47***	1.14***	1.56***
	(0.03)	(0.03)	(0.53)	(0.56)	(0.16)	(0.11)
Female	-2.38***	-2.30***				
	(0.09)	(0.07)				
Uber * Female	-0.02	-0.19*				
	(0.08)	(0.11)				
Black	-0.25***	-0.23***	-0.44***	-0.44**	-0.28***	-0.31***
	(0.05)	(0.05)	(0.15)	(0.20)	(0.07)	(0.09)
Married	0.11***	0.06**	0.25**	0.49***	0.23***	0.21***
	(0.03)	(0.02)	(0.12)	(0.12)	(0.03)	(0.04)
Age	0.04***	0.03***	0.05***	0.06***	0.05***	0.05***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Elementary School	0.58***	0.57***	0.29*	0.16	0.50***	0.49***
	(0.04)	(0.03)	(0.17)	(0.15)	(0.04)	(0.04)
High School	0.88***	0.89***	0.94***	0.94***	0.54***	0.58***
	(0.07)	(0.05)	(0.16)	(0.13)	(0.05)	(0.06)
College or higher	-0.20**	-0.15*	-0.09	-0.12	-0.82***	-0.68***
	(0.08)	(0.08)	(0.41)	(0.53)	(0.15)	(0.16)
Children ages 0 to 6 in the household	0.01	0.00	-0.14	-0.16	-0.09	-0.11
	(0.02)	(0.03)	(0.30)	(0.25)	(0.09)	(0.11)
Children ages 7 to 15 in the household	-0.02	-0.05	0.09	-0.03	-0.07	-0.15
	(0.02)	(0.04)	(0.09)	(0.11)	(0.08)	(0.11)
Children (0 to 6) * Children (7 to 15)			0.48	0.70	0.17	0.39***
			(0.29)	(0.46)	(0.14)	(0.14)
Uber * Black			0.22	0.27	0.04	0.11*
			(0.14)	(0.19)	(0.04)	(0.06)
Uber * Married			-0.11	-0.42***	-0.20***	-0.24***
			(0.16)	(0.11)	(0.04)	(0.05)

(Continue in the next page)

Table B7 (continued)

	All		Women		Men	
	Canonical	Staggered	Canonical	Staggered	Canonical	Staggered
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Uber * Age			-0.02*	-0.04***	-0.02***	-0.02***
			(0.01)	(0.01)	(0.00)	(0.00)
Uber * Elementary School			0.63*	0.83**	0.15***	0.18***
			(0.35)	(0.34)	(0.04)	(0.06)
Uber * High School			0.97***	1.11***	0.46***	0.45***
			(0.24)	(0.25)	(0.05)	(0.07)
Uber * College or higher			1.26***	1.34**	0.76***	0.70***
			(0.45)	(0.58)	(0.10)	(0.13)
Uber * Children (0 to 6)			-0.65***	-0.87**	0.23**	0.20
			(0.24)	(0.36)	(0.12)	(0.15)
Uber * Children (7 to 15)			-0.08	-0.24	0.10	0.16
			(0.20)	(0.30)	(0.13)	(0.13)
Uber * Children (0 to 6) * Children (7 to 15)			0.20	0.37	-0.41*	-0.57***
			(0.22)	(0.48)	(0.21)	(0.17)
Constant	-6.00***	-5.94***	-8.67***	-9.40***	-6.45***	-6.49***
	(0.05)	(0.08)	(0.39)	(0.27)	(0.12)	(0.11)
Observations	2,156,286	1,070,788	977,263	485,914	1,179,023	584,874
Pseudo R-squared	0.12	0.12	0.05	0.06	0.05	0.06

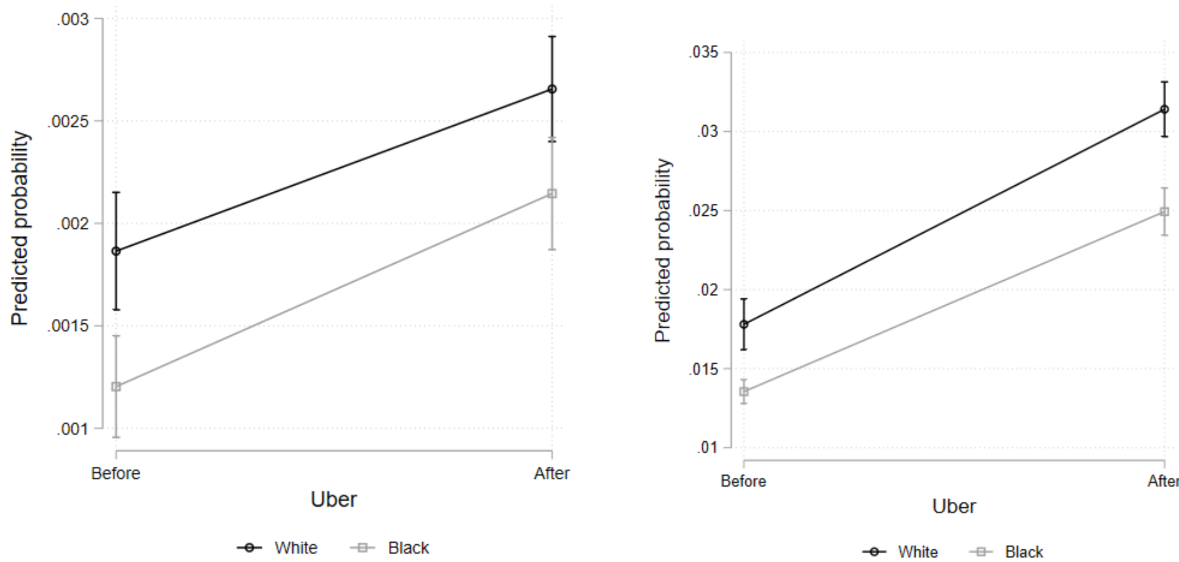
Note: Logistic regressions with self-employed driver as the dependent variable. In the canonical difference-in-differences specifications, post-ridesharing is equal to one for 2018-2019 and zero for 2012-2013. All models control for metropolitan and quarter fixed effects. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B8. Job Outcome Linear Models: Canonical versus Staggered Difference-in-Differences

	Log. Monthly Earnings		Log. Hourly Earnings		Weekly Hours Worked	
Variables	Canonical (1)	Staggered (2)	Canonical (3)	Staggered (4)	Canonical (5)	Staggered (6)
Uber	-0.21***	-0.29***	-0.13***	-0.20***	-3.47***	-4.08***
	(0.02)	(0.03)	(0.02)	(0.04)	(0.67)	(1.03)
Female	-0.32***	-0.41***	-0.04	-0.09	-11.04***	-12.26***
	(0.02)	(0.04)	(0.04)	(0.07)	(1.20)	(1.07)
Uber * Female	0.18***	0.29***	0.11**	0.15*	2.46**	4.97***
	(0.03)	(0.06)	(0.05)	(0.08)	(0.94)	(0.95)
Married	0.09***	0.06***	0.05***	0.04***	1.17*	0.67
	(0.03)	(0.02)	(0.01)	(0.01)	(0.68)	(0.54)
Black	-0.07***	-0.06***	-0.07***	-0.07***	-0.27	0.29
	(0.01)	(0.01)	(0.01)	(0.01)	(0.23)	(0.27)
Elementary School	0.17***	0.16***	0.11***	0.11***	1.86***	1.25*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.38)	(0.71)
High School	0.30***	0.29***	0.22***	0.23***	2.28***	1.62**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.46)	(0.72)
College or higher	0.47***	0.43***	0.41***	0.43***	1.80*	-0.17
	(0.02)	(0.03)	(0.03)	(0.03)	(0.90)	(1.04)
Age	0.00***	0.00**	0.00***	0.00***	-0.03	-0.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)
Children ages 0 to 6	0.05	0.05**	0.01	-0.02	2.07***	3.38**
	(0.03)	(0.02)	(0.03)	(0.04)	(0.62)	(1.26)
Children ages 7 to 15	0.03*	0.01	0.02	0.00	0.45	0.45
	(0.02)	(0.02)	(0.02)	(0.02)	(0.45)	(0.47)
Children 0-6 * 7-15	-0.07**	-0.06	-0.05	-0.01	-1.01	-1.97
	(0.03)	(0.04)	(0.03)	(0.04)	(1.04)	(1.71)
Constant	7.34***	7.50***	2.03***	2.13***	46.80***	49.22***
	(0.02)	(0.05)	(0.03)	(0.05)	(0.74)	(0.89)
Observations	27,640	15,518	27,640	15,518	27,640	15,518
R-squared	0.16	0.16	0.12	0.12	0.05	0.06

Note: Linear regressions with self-employed driver as the dependent variable. In the canonical difference-in-differences specifications, post-ridesharing is equal to one for 2018-2019 and zero for 2012-2013. All models control for metropolitan and quarter fixed effects. Standard errors clustered at the metropolitan area in parentheses. *** p<0.01, ** p<0.05, * p<0.1

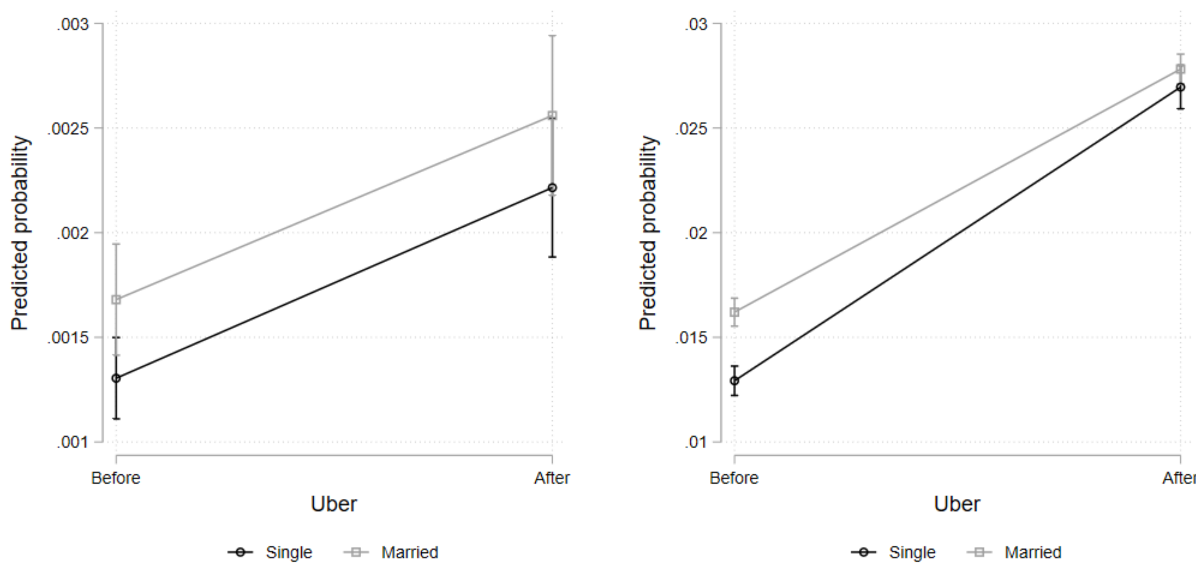
Appendix B Figures



a. Women b. Men

Figure B1. Predicted Probabilities of being a Self-Employed Driver by Sex and Race

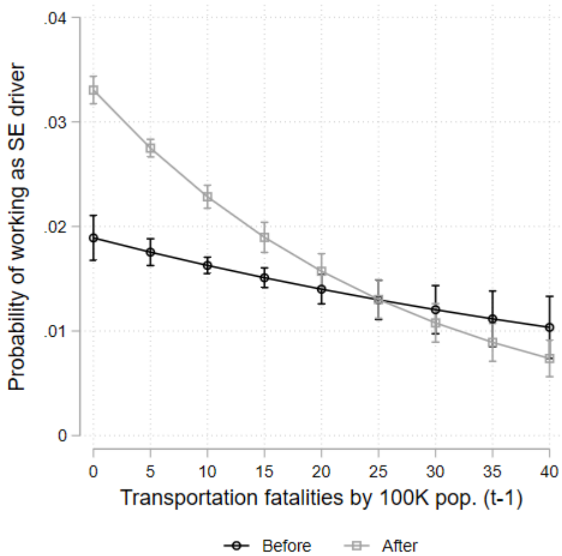
Note: Marginal predictions and confidence intervals of models in columns 2 and 3 in Table B3 in Appendix B.



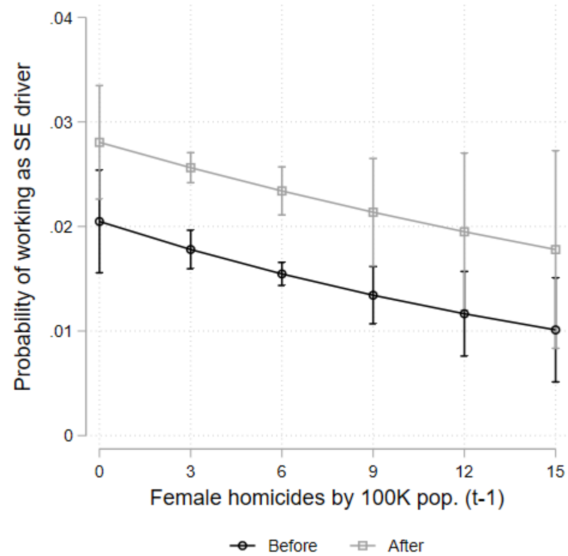
a. Women b. Men

Figure B2. Predicted Probabilities of being a Self-Employed Driver by Sex and Marital Status

Note: Marginal predictions and confidence intervals of models in columns 2 and 3 in Table B3 in Appendix B.



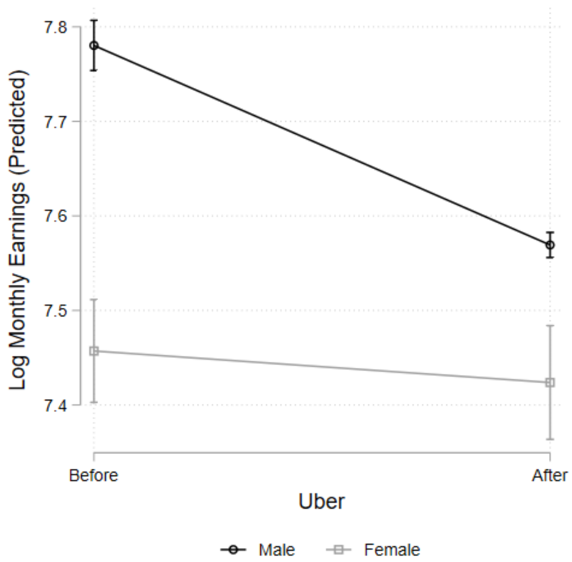
a. Transportation Fatalities

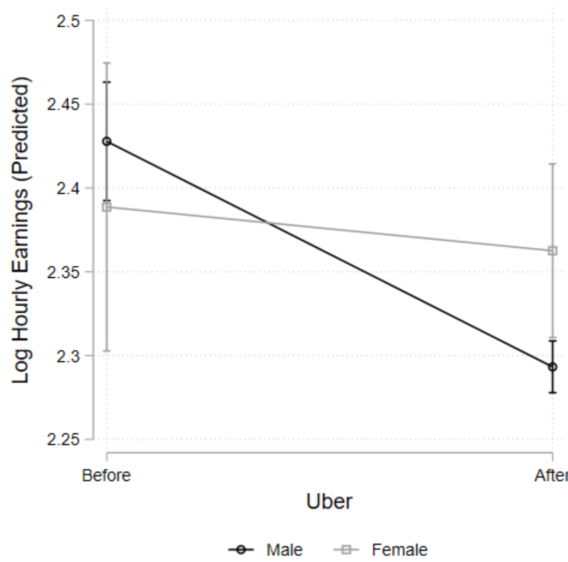


b. Female Homicides

Figure B3. Predicted Probabilities of Men being Self-Employed Drivers Before and After Uber

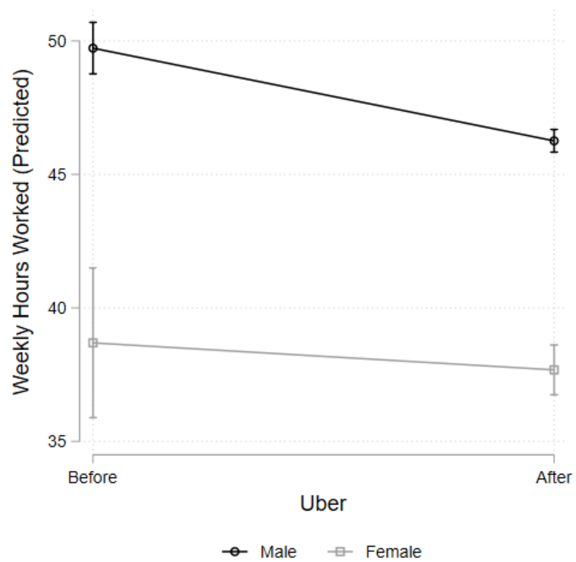
Note: Marginal predictions and confidence intervals of models in column 3 Table 2.





a. Log monthly earnings

b. Log hourly earnings



c. Weekly hours worked

Figure B4. Predicted Job Outcomes of Self-Employed Drivers by Sex

Note: Predicted values based on the regressions shown in Table 2.

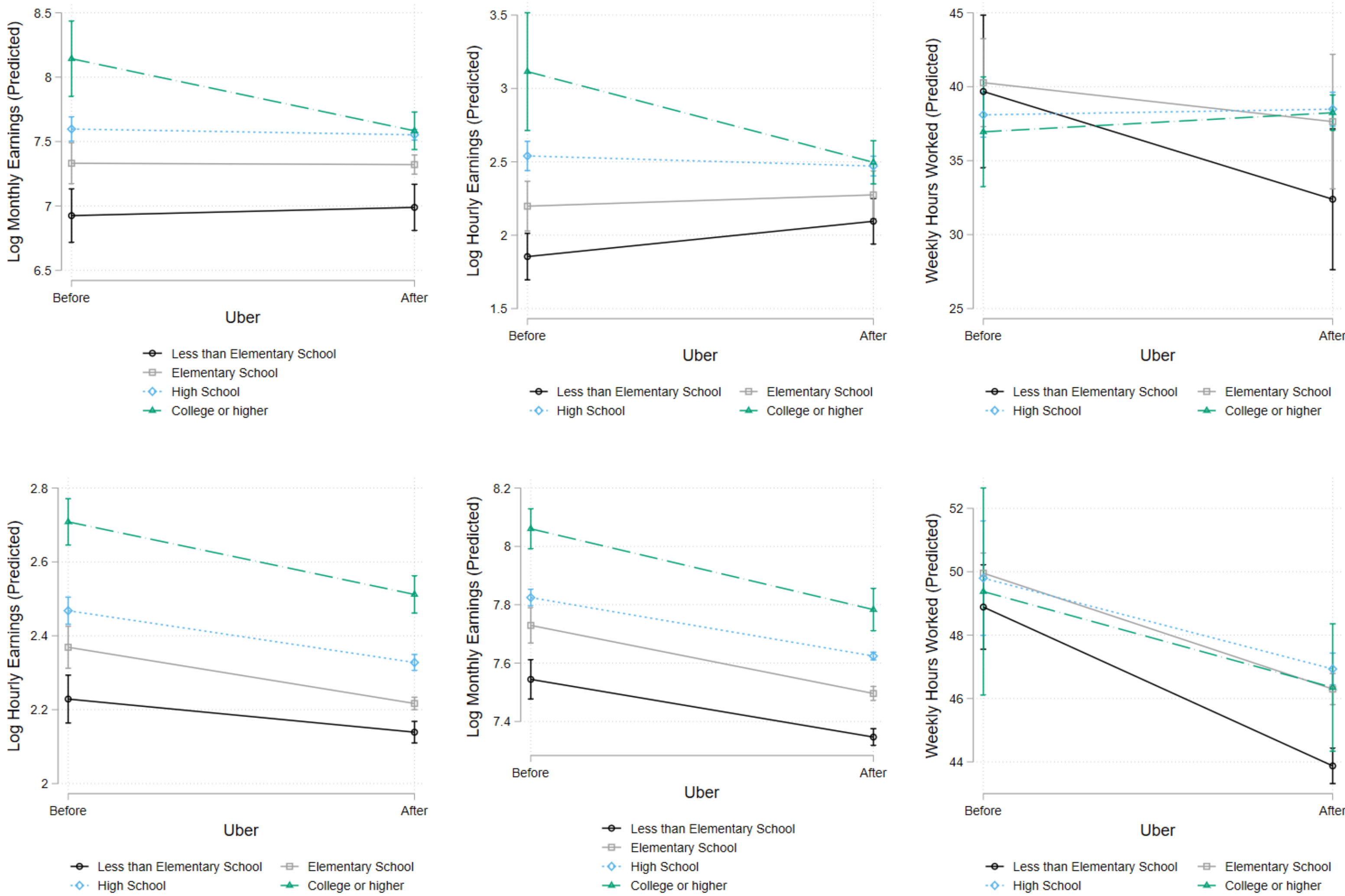


Figure B5. Predicted Job Outcomes by Sex and Education (Top panel: women. Bottom panel: men)

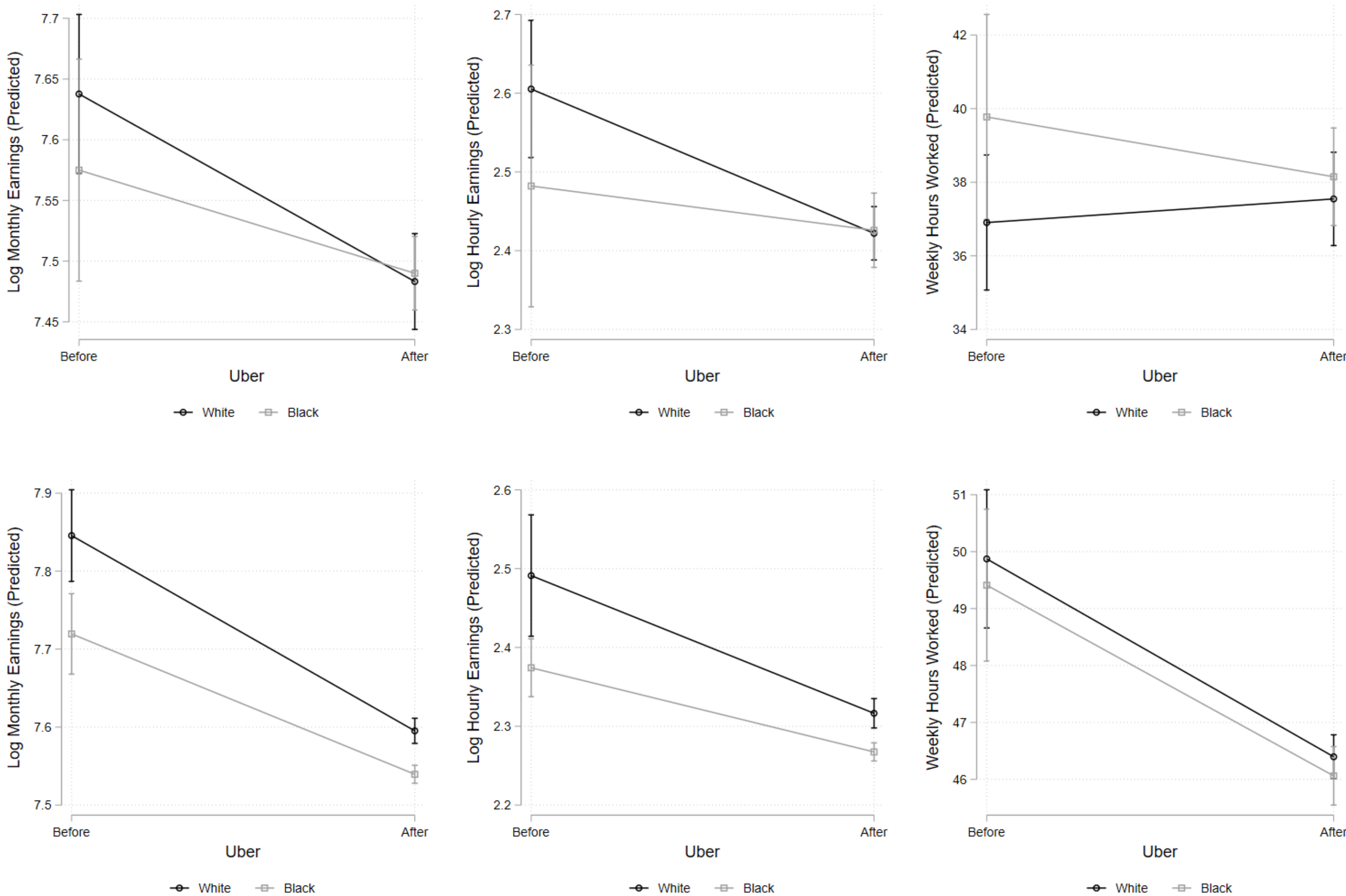


Figure B6. Predicted Job Outcomes by Sex and Race (Top panel: women. Bottom panel: men)

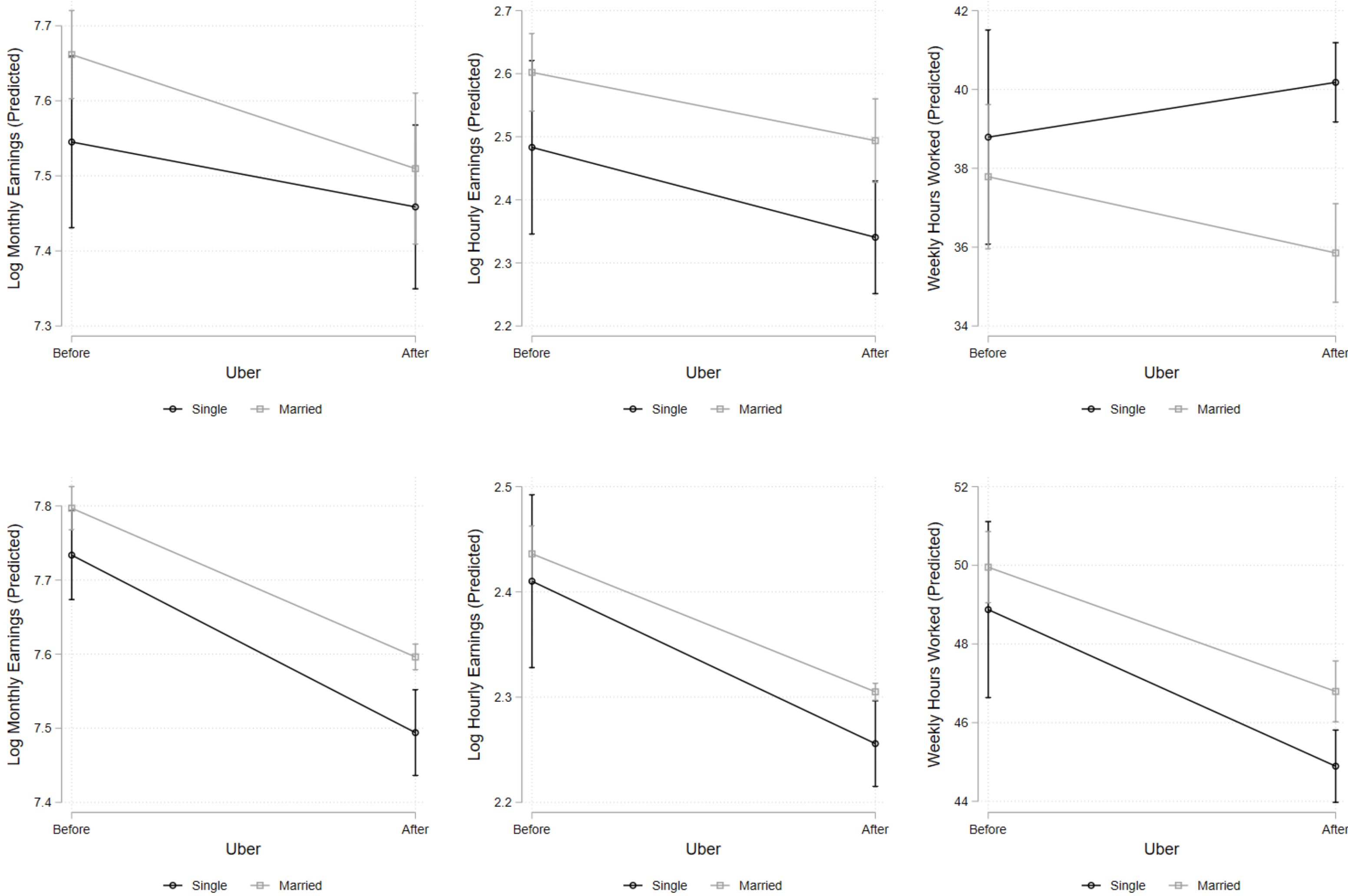


Figure B7. Predicted Job Outcomes by Sex and Marital Status (Top panel: women. Bottom panel: men)

Appendix C. Chapter 4 Supplementary Materials

Appendix C Tables

Table C1. Summary of Web-Scrapped Gigs by Category

Categories	Number of gigs (total)	Number of gigs (%)	Median starting fee	Mean starting fee	Unique sellers
Business	13,170	9.1	40	136	4,195
Data	2,003	1.4	25	86	721
Digital Marketing	12,896	8.9	25	116	6,003
Graphics & Design	27,355	18.8	20	66	13,910
Lifestyle	12,766	8.8	20	41	4,290
Music & Audio	15,521	10.7	25	55	6,376
Programming & Tech	14,447	10.0	50	175	4,659
Video & Animation	9,605	6.6	25	101	4,200
Writing & Translation	37,400	25.8	20	53	14,235
Total	145,163	100.0	25	83	58,589

Appendix C Figures

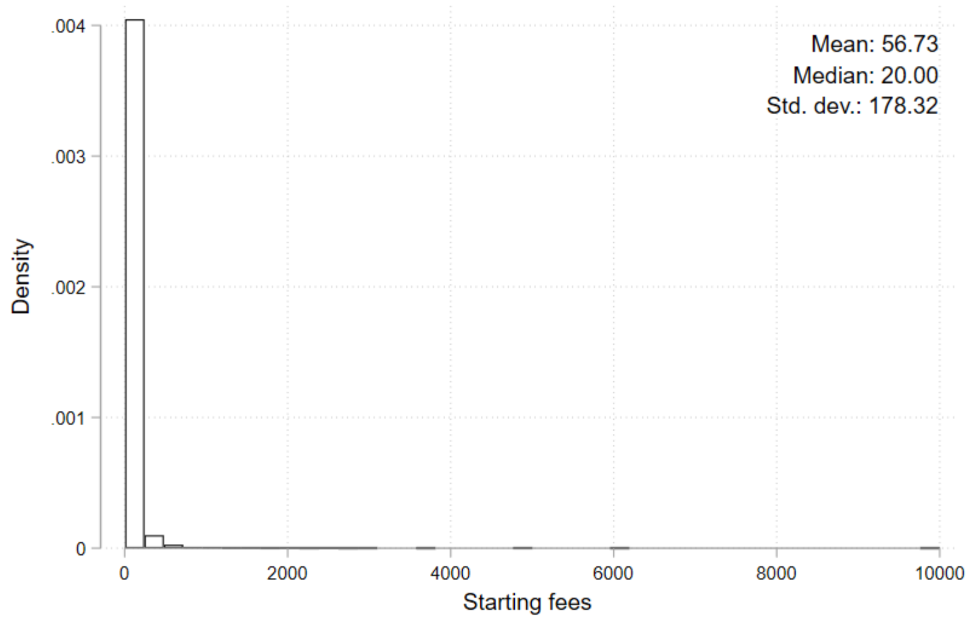


Figure C1. Seller Starting Fees (Active Sellers)

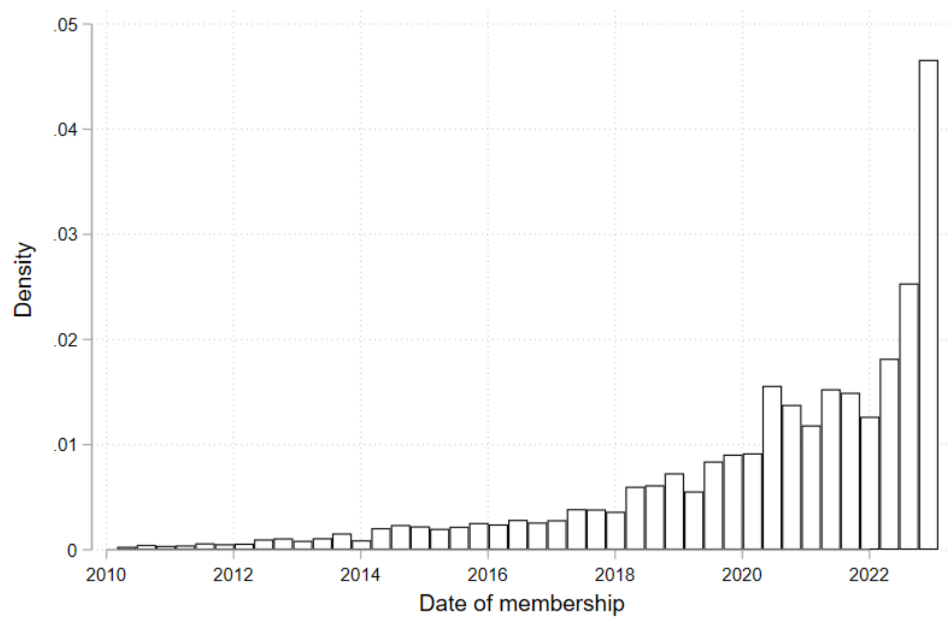


Figure C2. Date of Membership (Active Sellers)

Hello xxxx,

My name is Luisa Nazareno, and I am a Ph.D. candidate in Public Policy at Georgia State University. I am conducting a study on the preferences of people using platforms such as Fiverr for work.

I would like to invite you to participate! The study will occur one week from now (May 15) and take no more than 20 minutes of your time. At the end, you will receive a monetary reward of up to $45 dollars, paid through Fiverr.

This is an online study which will ask you to choose between two options in a series of rounds, followed by a short survey. There will be no questions that can reveal your identity.

If you are interested, please use the link below to schedule a time slot for your participation. The invitation expires tomorrow (May 09) at midnight (EST).

https://platform-study.herokuapp.com/room/fiverr3

Each invitation has a unique access code. Yours is: XXXXXX

I am also happy to answer any questions you may have.

Thank you!

Figure C3. Recruitment Message

Part III (1/2)

1. In addition to Fiverr, do you rely on other platforms to work?

- Yes
- No

2. Do you currently have another job non-related to platforms?

- Yes
- No

3. How many hours per week do you usually work on gigs obtained through Fiverr and similar platforms? (Please type a number)

4. How many hours per week do you usually work on all your jobs? (If you do not have off-platform jobs, please repeat the number above)

5. How long have you used platforms for work purposes?

- Less than a month
- Between one and six months
- Between six months and one year
- More than one year

6. Do you see yourself continuing to use Fiverr (or another platform) for work one year from now?

- Yes
- No

8. Please select the reason that best explains why you work for Fiverr.

- To be my own boss
- I would like to work more hours than allowed in my other job
- To supplement income on a regular basis
- To supplement income on a temporary basis or for a specific purpose
- To vary the type of task that I do for work
- Other

9. In your opinion, what is the main advantage of using Fiverr (and other online platforms) for work?

10. In your opinion, what is the main disadvantage of using Fiverr (and other online platforms) for work?

11. Under which Fiverr category do you have your gig listed?

- Business
- Data
- Digital Marketing
- Graphics and Design
- Lifestyle
- Music and Audio
- Programming and Tech
- Video and Animation
- Writing and Translation

Next

Figure C4. Survey (Page 1/2)

Part III (2/2)

12. What is your age?

13. What is your gender?
- ○ Male
- ○ Female
- ○ Other

14. What is your race?
- ○ White (non-latino)
- ○ Black (non-latino)
- ○ Asian (non-latino)
- ○ American Indian or Alaska Native (non-latino)
- ○ Latino
- ○ None of the above

15. What is your highest educational attainment?
- ○ Incomplete High School or Less
- ○ High School Degree
- ○ Some College
- ○ Bachelors degree
- ○ Graduate degree

16. What is your marital status?
- ○ Married / living with partner
- ○ Widowed
- ○ Divorced / separated
- ○ Never married

17. Are there any children ages 0 to 15 living with you?
- ○ Yes
- ○ No

18. Would you be interested in participating in a follow-up interview as part of this study?
- ○ Yes
- ○ No

19. If you would like to keep posted on the results of this study in the future, please type your email below. Otherwise, please type "No."

Congratulations!
You have now reached the end of this study. To conclude, one of the rounds will be randomly chosen for pay.

Find out my reward

Figure C5. Survey (Page 2/2)

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