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Three essays on digital platforms and their impact on labour

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The most beautiful sea
hasn't been crossed yet.
The most beautiful child
hasn't grown up yet.
Our most beautiful days
we haven't seen yet.
And the most beautiful words I wanted to tell you
I haven't said yet...

Nazim Hikmet

To the struggling people of Palestine, and to my grandparents.

Abstract

Digital platforms have driven a structural transformation of Italian labour markets, with consequences for workers. This thesis examines three settings in which platform diffusion has reshaped employment and earnings, and argues that the common thread is a worsening of working conditions through lower wages and rising precariousness. The first essay uses administrative tax data from MEF-Irpef at the municipal level to estimate the effects of Amazon's entry into Italian local labour markets. Exploiting the staggered opening of Amazon warehouses across municipalities, I find that Amazon presence causes significant declines in local wages and no increase in employment. The second essay draws on firm-level data from INAPP-DPS and shows that, within the hospitality and restaurant sectors, adoption of digital platforms leads to a higher share of non-standard employment. The third essay uses worker-level data from the INAPP-PLUS survey and documents that participation in online labour platforms is associated with lower earnings through unevenly distributed working hours and increases in lower-paying tasks associated with platforms, such as cleaning, food delivery, and micro-working. Taken together, the three essays show that platform diffusion in Italy has not been a neutral force of technological change: the power platforms exert has increased risk and compressed earnings for the workers most exposed to it.

Keywords: digital platforms, labour, flexibility, platform work

Contents

List of Figures

List of Tables

Introduction

This thesis is the result of four and a half years of research on digital platforms. The platform is the archetypal form that the most successful firms in the 'tech' industry have taken. Firms such as Google, Facebook, Amazon are platforms, as well as very successful sectoral upstarts, transformed overnight into global players – for example Uber, Airbnb, Booking. These firms combine deep investments in software and market share with asset-light balance sheets; hire very few direct employees, yet command and organise the everyday economic and social activities of millions – and sometimes billions – of people.

Over the course of the last twenty years, their names have become brands, and their influence has grown so as to influence institutions. However, the consequences of the widespread expansion of platforms, carrying with them profound organisational, social and economic transformations, were, at the beginning of this research, not quite well documented. While the issue had been framed by books and reports in many different fields (Gawer et al., 2002; Rochet and Tirole, 2003; Huws, 2014; Kenney and Zysman, 2016; Khan, 2016; Srnicek, 2017; Graham et al., 2017; Pesole et al., 2018; Belleflamme and Peitz, 2021; Aloisi and De Stefano, 2022), very few studies had access to large and reliable datasets. At the intersection between platform and labour studies, in particular, available empirical evidence focused primarily on platforms intermediating labour. Platform workers (drivers, riders, clickworkers) were a new phenomenon: this workforce, albeit relatively small in relative size, appeared poised to expand and represented a glimpse of possible future developments encompassing the whole economy (Schor and Attwood-Charles, 2017; Guarascio and Sacchi, 2018; Berg et al., 2018; De Groen et al., 2018). Later, it would have become understood that platforms could not intermediate, directly, large parts of the labour force, but rather that they were capable of influencing how work was performed also in more "traditional" settings, fitting into a larger drive towards the flexibilisation of employment relationships across industries and countries in the developed world (Vallas and Schor, 2020; Jarrahi et al., 2021; Baiocco et al., 2022; Fernández-Macías et al., 2023).

Platforms were also the means through which advancements in the IT paradigm (Freeman et al., 1988) were expressed at the level of industrial organisation, thereby also influencing labour indirectly through the shift towards small-size, capital-intensive, high-productivity firms at the expense of relatively more labour-intensive products and services, resulting in a redistribution of the welfare gains of production away from workers and towards capital-owners (Autor et al., 2020).

The challenge then became two-pronged. First, from an empirical point of view, there was a need to retrieve and exploit larger and more official sources of information that were beginning to be collected at the country-level by statistical offices (Bergamante et al., 2022; Fernandez Macias et al., 2025). Secondly, from a conceptual perspective, it had become apparent that it was necessary to go beyond approaches that measured the influence of platforms on labour through direct intermediation. Instead, also the labour consequences of platform presence at the level of the firm must be observed (Cutolo and Kenney, 2021; Centra et al., 2024) and at the level of the local labour market platform power had to be assessed (Chava et al., 2024; Bauer and Fernández Guerrico, 2023), so as to capture the impacts platform were having by effect of the technological innovations, and the socio-technical power structures, introduced by them.

Relying on different econometric methods (regression analysis, difference-in-differences), applied to three Italian data sources (two of which novel and unique), the present work aims to contribute to fill the two gaps: exploiting new data sources and expanding the understanding of platforms' influence on work. Platforms are analysed through a magnifying glass: first, their impact on local economies is examined, by observing the deployment of platform-related physical infrastructure in Italian territories, distinguishing between urban and rural contexts; second, the influence platforms have on firms and their workers is assessed using the Digital Platform Survey, an original data source from the National Institute for Public Policy Analysis (INAPP);[1] lastly, a recognition of the impact platform have on workers mediated through them is performed to highlight newly emerging heterogeneities.

The main results highlight how, as digital platforms gain substantial capacity to alter the economies in which they become embedded, workers' economic condition worsens. Digital platforms, while they contribute to the spread of innovations, appear therefore as the agents of a wider economic transformation, one that consists in increasing inequality levels and the erosion of labour market institutions.

In what follows, this introduction first provides an overview of the theoretical framework employed. Thereafter, the three essays constituting the chapters of the thesis are shortly summarised.

What are digital platforms?

Digital platforms benefit from key enabling technologies, such as the smartphone and recommender system algorithms. More broadly, they are the organisational form of the contemporary technological paradigm (Freeman et al., 1988). Most platform markets are based on the pivoting of a network around a single firm for efficiency purposes (think of Google, or Amazon), as the firm coordinates and shapes the relationship between agents (consumers, vendors, advertisers, publishers, etc.) (Kenney and Zysman, 2016). Therefore, platforms are involved in strong dynamics of power accumulation and rent extraction, deriving from their centrality but also from deliberate strategic positioning (Srnicek, 2017). Relatedly, platforms operate a strategic reallocation of productive factors in the sectors in which they are embedded, predating and substituting existing power and control structures (Coveri et al., 2022).

The literature on digital platforms offers a plurality of definitions. In economics, Rochet and Tirole (2003) identify platforms as entities that must connect at least two sets of actors in a market, acting as intermediaries between distinct groups of users and generating value through cross-network externalities. A similar perspective is present in later work, emphasising reductions in transaction cost and the power of platform intermediaries to leverage their centrality, with the objective of gathering and deploying information to finance their activities and profit from market interactions

[1] `https://www.inapp.gov.it/en/institute`

(Acs et al., 2021; Belleflamme and Peitz, 2021). Kenney and Zysman (2016), alongside others (Gawer et al., 2002; Gawer, 2014; Parker et al., 2016; Cusumano et al., 2019), first highlight the salience of the platform organisation for the digital age, capable of creating and capturing value thanks to pervasive connectivity and globalised digital innovation. They also introduce agency on the part of the platform in defining the rules of engagement: platforms do not simply create and manage a network, they shape the terms on which participants interact with one another.

The pervasiveness of digital platforms, and the technologies with which they are endowed and deploy, allows them, critically, to externalise responsibility (Vallas and Schor, 2020; Stark and Pais, 2021). Platforms thus exercise control over economic transactions while still concentrating power, constituting a governance mechanism distinct from markets, hierarchies, or networks.

Platforms are thus monopolistic undertakings, which act to influence the surrounding environment beyond the boundaries of the firm. Coveri et al. (2022) and Rikap (2021) argue, from different perspectives, that platforms are the natural heirs of transnational corporations, employing new means and methods to plan production into a single, strategic decision-making centre. The latter focuses on intangible capital accumulation as the main lever of power for intellectual monopolies (Rikap, 2021). The former, using Amazon as a case study, highlight the control the platform exercises over workers, suppliers/vendors, societies and governments. Their perspective does not limit power and control to market relations, but extends the dominance of platforms to global production, societal norms, national and international law (Coveri et al., 2022). The platform does not simply dominate firms and suppliers through diversification and direct control of data and technology, but also exercises a "panopticon" form of control over value chains, learning from partners' business practices and enhancing its own innovation capabilities with little cost.

Yet, digital platforms do not merely redraw the rules of competition, and the relations between core firms and suppliers. They also produce deep structural impacts on labour markets and incumbent firms. For example, Chava et al. (2024) show that the expansion of Amazon distribution centres reduces the incomes of traditional retail workers in geographically proximate counties. The dynamic operates through the direct substitution of labour through automation and algorithmic reorganisation of tasks and the marginalisation of incumbent firms, which find themselves competing against operators with structural advantages in scale, data and capital. The concept of technological innovation carried by platforms therefore entails a redistribution of economic power that systematically favours new digital entrants at the expense of established actors in traditional sectors. Platforms emerge not only as engines of advancement and innovation, but also as agents of a neo-liberal technological and economic paradigm that simultaneously produces inclusion for those who adapt to it and exclusion for those unable to assimilate. In this sense, a platform does not merely connect actors already integrated into a shared paradigm: it also transforms, subordinates or marginalises those sectors, territories and workers that do not recognise themselves in the model of control and innovation it imposes.

At the phenomenological level, a platform is a set of practices through which control and power are acquired — over the infrastructures of interaction, over workers, over suppliers, and over the sectors in which the platform operates. This power is not exercised in a single register. It rests on the apparently neutral coordination and governance of interactions described by the economic literature (Gawer et al., 2002; Rochet and Tirole, 2003); it is consolidated through the explicit, monopolistic control that platforms exercise by means of their devices, technological schemes and command over interaction flows (Rikap, 2021; Coveri et al., 2022); and it reaches, more diffusely, into the systemic disruption that platform-led innovation produces in the sectors the platform enters, where incumbent structures are displaced and substituted (Srnicek, 2017; Parker et al., 2016; Chava et al., 2024).

Digital platforms connect and coordinate agents algorithmically, exert power over those connections assimilating the participants' prerogatives, and disrupt non-digital structures and intermediaries.

How do digital platforms work?

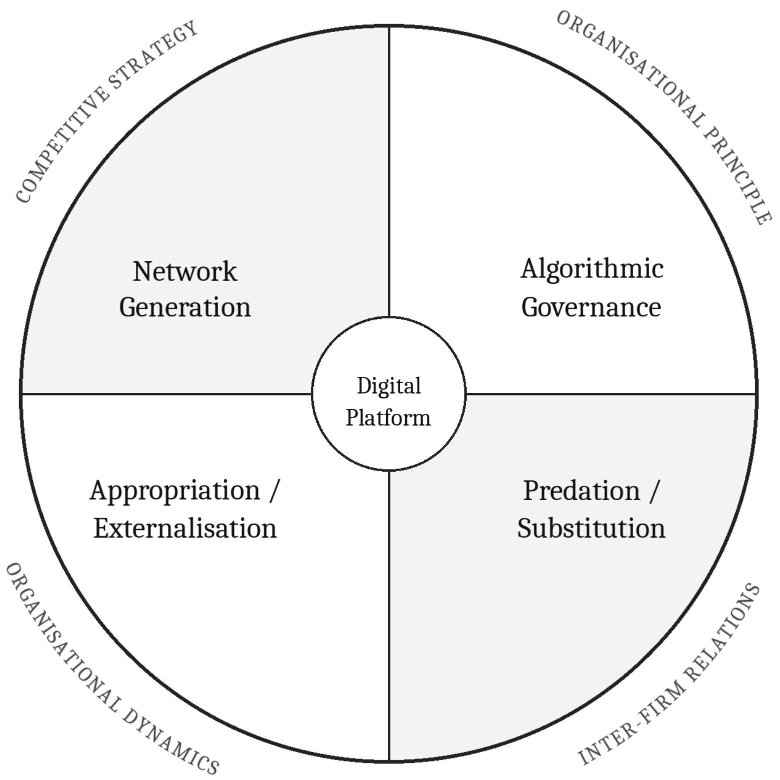
Platforms facilitate the search for products, friends, and customers. Similarly, they provide suitable venues to scale business operations by reducing transaction, transportation, monitoring, and other costs (Shapiro, 1999; Goldfarb and Tucker, 2019; Acs et al., 2021; Dolfen et al., 2023).

Platforms operate through network effects: the value of the service for each user grows as the overall number of users increases (Rochet and Tirole, 2003). It is important to distinguish between direct network effects — in which value increases as users on the same side grow, as in the case of GitHub, or Facebook — and indirect network effects, in which the value for one side increases as the other side grows, as in the case of Amazon or Youtube, where more sellers and videomakers attract more buyers and viewers and vice versa (Belleflamme and Peitz, 2018; McIntyre and Srinivasan, 2017; Parker and Van Alstyne, 2018). These market dynamics tend to produce winner-take-all or winner-take-most markets, in which users find it rational to concentrate on a single platform rather than fragmenting their activity across multiple services. The result is a strong tendency towards concentration and the accumulation of power by the dominant platform (Coveri et al., 2022; Wu, 2020).

Platforms incorporate into their operations data-intensive algorithmic management systems and concepts that define implicit rules of functioning, orienting the behaviour of agents — workers, suppliers, consumers — towards the outcomes desired by the platform (Pesole et al., 2018; Stark and Pais, 2021; Stark and Vanden Broeck, 2024). Algorithms do not merely coordinate transactions, but function as instruments of governance: they define incentives and determine access to opportunities within the "ecosystem" generated by the platform's infrastructure. For instance, a platform's algorithm determines firms' sales according to product relevance, quality (measures through reviews and ratings), price, and other factors (Resnick and Varian, 1997; Chen and Tsai, 2023). A crucial element is algorithmic opacity: agents are subject to rules they only partially know nor can contest, amplifying the power asymmetry between platform and users (Zuboff, 2019; Graham et al., 2017; Vallas and Schor, 2020).

Through algorithmic management, platforms hijack central functions of the productive and exchange process, maintaining strategic control over the underlying technological infrastructure. This infrastructure is simultaneously intangible — algorithms, software, artificial intelligence models, data architectures — and material: data centres, logistics networks, warehouses, hardware devices (Van Dijck et al., 2019; Plantin and Punathambekar, 2019; Rikap, 2021; Frapporti, 2024). Control over this infrastructure allows platforms to accumulate substantial quantities of data on agent interactions, data that are then redeployed to refine algorithmic mechanisms, improve products and reinforce barriers to entry against competitors (Ezrachi and Stucke, 2016; Sadowski, 2019; Belleflamme and Peitz, 2021). This feedback loop connects with the network effects discussed above,

Figure 1: How platforms work: main characteristics



further amplifying the winner-take-all tendency and entrenching platforms at the centre of the economy. The ownership of infrastructure distinguishes platforms from simple intermediaries, merely facilitating transactions. Platforms instead define the very conditions under which transactions take place.

The centralised control of strategic infrastructure mirrors a tendency to externalise labour and capital not considered essential to the platform's core operations. The platform deliberately relinquishes ownership of peripheral productive factors, transferring risks and costs onto the agents of its ecosystem (Ietto-Gillies and Trentini, 2023; Butollo et al., 2022). What should not be appropriated is subsumed indirectly: formally external, but in practice subordinated to the platform's algorithmic rules (Srnicek, 2017; Coveri et al., 2022). This logic allows platforms to scale rapidly while minimising fixed capital. Appropriation and externalisation are not contradictory mechanisms, they are complementary and strategically coordinated. The platform controls data, core hardware, and algorithms generating structural power and externalises costly and risky assets — labour, physical capital. Such a combination renders the platform business model extraordinarily efficient from the standpoint of accumulation (Parker et al., 2016; Cusumano et al., 2019; Coveri et al., 2022).

Platforms finally pursue the strategic objective of displacing the mature sectors into which they insert themselves, absorbing and dominating markets (Srnicek, 2017). They simplify and stream-line existing procedures — lowering transaction costs, reducing informational frictions and making previously complex or segmented services accessible — thereby rapidly gaining market share at the expense of traditional operators (Goldfarb and Tucker, 2019; Acs et al., 2021). Thus, they structurally undermine the latter's sources of revenue, exploiting the competitive advantages derived from data control, algorithmic scalability and the ability to operate through cross-subsidisation (Belleflamme and Peitz, 2021) across different segments of their ecosystem. The process is also predatory: platforms frequently operate at a deliberate loss in order to eliminate competition (Khan, 2016), drawing on reserves of venture capital that traditional operators do not possess (Cusumano et al., 2020); once a dominant position is achieved, conditions for users and workers tend to deteriorate systematically (Doctorow, 2025). The result is a profound transformation of sectoral structure.

The power accrued by the most successful platform firms results in a transfer of value from less productive capital – obsolete or subsumed firms and industries – to more productive capital – the platform –, and from labour – substituted or algorithmically governed workers – to capital. Significantly, this contributes to inequality: platforms are, *per se*, superstar firms (Autor et al., 2020). They enjoy higher productivity with respect to their counterparts. They are also able to influence institutions around them through their market power, thus enjoying an advantage in bargaining vis-à-vis their workers and the state (Kumar, 2020; Coveri et al., 2022). Hence, the platform economy is strongly related to the fall of the labour share and, more precisely, to a number of significant changes to how work is performed, organised, and remunerated.

How do digital platforms influence labour?

Platforms bring significant changes to the world of work. Four trends can be identified: compression/polarisation, fissuring, augmented control, and substitution.

First, platforms foster wage compression for all workers, on the one hand, and the polarisation of these workers within the platform, while granting to a small subset of workers high wages and managerial powers (Garcia Calvo et al., 2023). Wage compression may occur in two ways, depending on the degree of routinisation of the job the platform requires or intermediates. Routinary tasks can be automated, leading to higher substitutability and deskilling tendencies within occupational groups such as logistics workers and content moderators (Delfanti, 2021a; Roberts, 2014). These workers are indirectly related to the platform's main mechanisms of labour intermediation; nonetheless, they are platformised through the use of digital monitoring tools, gamification, and algorithmically managed (Fernández-Macías et al., 2023). Non-routinary tasks are instead usually mediated through digital labour platforms (Berg et al., 2018; Pesole et al., 2018) employed for food couriers, drivers, cleaners, caretakers, micro-workers, but also freelance programmers, architects, and other professionals. These platforms tend to compress wages by retaining the power of defining/nudging prevailing pay rates, imposing commissions, and shaping competition for tasks within their interface (Huws et al., 2017; Cirillo et al., 2023a). The latter element, absent regulations on working hours or hourly wages, also leads to the partial polarisation between a small "élite" of overtime/over-productive workers and a "mass" of low-wage low-hours labourers (Bonifacio, 2023). The platform also fosters polarisation in a second manner, reminiscent of previous IT enterprises. As it manages its ecosystem and applications relying on an exiguous workforce, these workers become strongly rewarded and also – usually – enjoy stakes in the firm (Garcia Calvo et al., 2023).

Second, platforms contribute to workplace fissuring (Weil, 2015), as contractual fragmentation becomes a general characteristics of platform jobs and also consequence of platform entry in an established industry. Flexible employment relationships, hailed as means to redefine boundaries between labour and leisure decisions (Sundararajan, 2016; Schor and Attwood-Charles, 2017), often have resulted in enhanced precariousness for workers who rely on platforms for essential income (Vallas, 2019; Aloisi, 2022). These workers are often considered self-employed. As such, they enjoy fewer labour rights than their non-platform counterparts, yet they are not allocated more freedom to choose their occupation or working hours. Similarly, workers employed by firms conducting their business with the platform (suppliers and vendors) may, at least in part, bear the brunt of the uncertainty generated by the platform's management practices and business strategies. Also workers hired directly by the platform to perform essential operations under more stable contracts experience some level of fissuring in the form of gamification, dwindling working hours, overtime requests – resulting in high levels of turnover (Delfanti, 2021b).

Third, platforms often make use of disciplining mechanisms to ensure worker participation, and/or seller firm supply. Rankings, based on ratings and reviews, constitute the backbone of algorithms allocating work or making (semi-)automated decisions on labour and product contracts (Stark and Vanden Broeck, 2024; Orlikowski and Scott, 2014). This third trend contributes to a condition in which workers are *de facto* controlled by the platform, which is however able to eschew responsibility and coopt other groups (e. g. consumers) in disciplining work. This type of algorithmic management (Stark and Pais, 2021; Baiocco et al., 2022; Jarrahi et al., 2021; Wood, 2021) has also spilled over to traditional firms in industries where platforms are present (Fernández-Macías et al., 2023; Fernandez Macias et al., 2025)). The platform does not directly enforce its regime of high-productivity and enhanced control: rather, it makes use of digital monitoring tools (smartphone and browser applications, proprietary GPS, bracelets, other wearables) which encourage workers to keep a certain pace or to perform an activity in a predetermined, efficient mode (Zuboff, 2019; Gonzalez Vàzquez et al., 2025).

Fourth, platforms impact the broader economy. As industries witness the rise of platforms, they face difficult choices. They are either substituted by the platform firm, as is the case for small brick-and-mortar retail after Amazon (Chava et al., 2024), or they adopt some of the platform's characteristics (e.g., logistics: Cirillo et al. (2024a)). This process of platformisation impacts workers in legacy industries, with consequences on working conditions, but also on the degree of control enjoyed by the workforce, resulting in bargaining power losses (Fernández-Macías et al., 2023; Aloisi, 2022). The disruptive power the platform implicitly exerts becomes functional to sectoral restructuring and fosters occupational decrease. The platform partially hires back the workers it displaces: however, it does so unevenly across industries and territorial labour markets, and enjoying higher command of the demand for labour – monopsony power (Card, 2022).

Three essays on the labour impacts of digital platforms

Three different essays, constituting the three chapters of this thesis, address the impacts platforms have on work. In all three cases, the three types of power platforms exert upon the agents they orchestrate are intertwined. In the first case, the main power at work appears to be the implicit power of substitution platforms enjoy, and the related renewed dominance imposed upon the reorganised value chain. In the second case, it is most apparent that platform have a "neutral" power

Table 1: Labour impacts of platform power

Compression	Fissuring	Control	Substitution
- Routinary tasks become more substitutable	- High job precariousness of platform workers	- Ratings, reviews, rankings	- Pressure on traditional sector workers
- Platform intermediation, orchestrated competition of non-routinary tasks	- Unstable employment relationships for platform-dependent firms' workers	- Automated decision-making by algorithms	- Adaptation often resulting in lower bargaining power
- Overworked "élite", underpaid "mass", empowered architects	- Frequent overtime, high turnover for directly employed workers	- Digital monitoring through wearables and communication tools	- Digital platform monopsony

deriving from their centrality, but also that the deliberate imposition by them of unfavourable conditions may lead to the use of relatively more abundant non-standard employment relationships, and that implicitly platforms are displacing those workers and firms which do not adapt to this paradigm. In the third case, platform power is evident in its relationship with workers' economic conditions: platforms generate unregulated markets in which workers do not compete fairly, resulting in their insecurity as to hours worked.

All three essays focus on Italy, at different levels. The first essay analyses platform impacts on local labour markets, focusing on the distinction between urban and rural settings, marked by different types of Amazon facilities, and between low-income workers and middle-/high-income ones. Italian urban areas, where consumer demand is most present, appear the most impacted by platform presence. The second essay focuses on Italian firms in hospitality and restaurants, two industries with low value added and high rates of non-standard work, but also very relevant in the Italian public discourse. Where platforms are more present and central to value creation, as in the hospitality industry, worker precariousness is most evident. The third essay analyses individuals self-reportedly working for platforms in Italy, before and after the Sars-Cov-2 pandemic. It does not find strong evidence that, after-Covid, platform workers experience significantly different conditions from those enjoyed before; however it documents lower hours worked, little benefit in working overtime, and higher economic insecurity with respect to the rest of the population.

To conclude this introduction, the three chapters are briefly summarised.

A platform's impact in local labour markets

The first chapter observes local labour markets in Italy in which Amazon sets up a new facility, and estimates the impacts in terms of wages, employment, and the distribution of income. Amazon is found to have generally negative impacts on wages, while its impact on employment is less clear.

Amazon is a digital platforms, but is also part of the broader disruptions operated in retail and logistics with the development of larger malls, and then with the arrival of e-commerce. The digital platform is portrayed as having a three-pronged impact on the labour force: *prima facie*, it creates jobs in logistics and transportation; secondly, however, it is able to exert unprecedented economic power towards its labour force and the one it subcontracts - through temp agencies and third-party companies; finally, it is an agent of acceleration in the disruption of legacy brick-and-mortar retail, from small stores to larger chain shops.

Amazon operates two main types of facilities. Fulfillment Centers (FC) deal with the distribution of large stocks of merchandise, while Delivery Stations (DS), located closer to urban dwellings, deal with the last-mile. Amazon workers are mostly concentrated in FCs, while DSs employ less people. Also, the types of jobs Amazon creates are less stable and in a low-wage category; those that are replaced by it may be more lucrative, such as being a small shop owner.

Two research questions are drawn from theory. First, what is the impact of Amazon on wages and employment, and does this impact differ between FCs (rural) and DSs (urban)? Second, how does Amazon presence affect the income distribution? To answer them, the chapter adopts a staggered difference-in-differences strategy to estimate the impact of a new FC or a new DS on the average labour income, the number of people employed, and the income brackets of municipalities located in the corresponding EU-harmonised Labour Market Area.

Results indicate that the average impact of Amazon is negative on wages, and is neutral on employment. Urban labour market areas, marked by the presence of DSs, drive the results. Fulfillment Centers, located in more peripheral areas of Italy, do not have generally negative impacts on wages, but the population of low-wage earners increases in the area, at the expense of high-wage income earners.

Platform-dependent firms' workforce decisions

The second chapter turns its attention to workers in firms which use platforms. As platforms that serve as aggregators of smaller businesses possess superior technical and economic means, they have an incentive to at least partially exploit this asymmetrical relationship. At first, a platform provides an easily accessible online market outlet for a firm with low digital capabilities, and aims to favour firm presence to kickstart network effects. Once dominance is established in the relevant market, however, the platform can charge fees for placement, and otherwise manage the relationship with the businesses so as to maximise its revenue.

As platform-dependent firms become more vulnerable to the decisions of the platform, they can adopt different strategies. Some of them deal with mitigating of the platform's impact, through multi-homing (using different platform outlets), ads campaigns, or the development of autonomous, alternative capabilities. Another strategy is however to adapt to a more uncertain environment by adjusting the ratio of flexible employees in an organisation. In this way, platform-dependent firms pass through part of their uncertainty to workers.

Services represent an interesting setting to study this phenomenon. Historically characterised by high levels of seasonal and non-standard work, businesses in hospitality and restaurants have embraced digital platforms to fulfil the need for online placement, reviews, reservations, and food delivery. Platforms in these industries have rapidly developed, particularly in hospitality.

The chapter then aims to answer the question of whether these businesses, when using platforms, employ a higher share of workers under non-standard employment relationships. Further, interpreting the use of non-standard workers as a proxy for higher uncertainty, it asks whether certain mediating factors can magnify or reduce the impact of platform dependence.

Three econometric exercises are built using an original, administrative data source, the Digital Platform Survey (DPS), which contains information on digital platform use, turnover, investments and labour contracts of a representative sample of Italian businesses. The first econometric exercise estimates the direct relationship between platform use and non-standard employment relationships, strengthening the interpretation through a Coarsened Exact Matching and using lagged variables. The second exercise focuses on the population of platform users, estimating the effect of size (as increasing bargaining power), multihoming (to mitigate adverse impacts of dependency), using the leading platform (which could impair autonomy) and engaging in platform-related investments (amplifying lock-in). The third exercise, used as a robustness check, is a Coarsened Exact Matching-augmented difference-in-differences estimation on the impact of platform adoption on the subset of 2020 adopters.

The chapter provides evidence of higher levels of organisational flexibility for workers in hospitality firms and restaurants which use platforms. The impact is mitigated by larger firm sizes and by the use of multiple platform, while it is magnified by a relationship with a monopolistic platform and by stronger platform lock-in, such as the one generated by platform-specific investments. The quasi-causal interpretation of the relationship between platform adoption and non-standard work is strengthened both by the use of Coarsened Exact Matching and by the difference-in-differences results.

As instability permeates platform markets (for products and labour alike), one of the outcomes deriving from the conditions of actors depending on digital intermediation is economic insecurity. The increased flexibility/precariousness observed in firms using platforms mirrors the experience of workers directly intermediated by platforms.

Platform workers' economic conditions

The third chapter concerns workers who perform work directly through a digital labour platform. Platforms such as Uber, Amazon Mechanical Turk, or Deliveroo intermediate workers in the gray area between self-employment and a direct employment relationship. These workers therefore suffer from intermittent working patterns, leading to low pay and economic insecurity. The chapter thus aims to assess the relationship between these two elements and the performance of work through a platform. Further, as the relevance of platform work has increased after the Covid-19 pandemic, it is important to understand whether the nature of the work performed has also shifted for the new cohorts of workers entering platforms after 2020.

The economic conditions of platform workers have been explored extensively. Yet, several gaps in the literature are present. First, there is a need to go beyond specific case studies on a single platform work category or undifferentiated platform work definition. Second, the main mechanisms through which platforms allocate gigs and foster income uncertainty lack an empirical verification. The chapter aims to address these gaps in two ways. First, it points at the common traits and heterogeneities between platform workers performing different tasks. Second, it analyses the interplay between platform work and the amount of hours worked. As platforms orchestrate competition between workers and allow free entry of new workers on their interface, the average number of tasks assigned to workers may decrease; however, given that platforms do not have limitations on the number of hours any single agent can work, a few workers receive ever more tasks.

Using two waves of the Italian Participation, Labour, Unemployment Survey (PLUS), containing information on platform workers' household incomes, alongside their characteristics, compared with the rest of the population, the research is developed through eight econometric exercises. An ordered probit on incomes with platform work as the main explanatory variable is followed by a probit on the likelihood of having postponed medical treatment for financial reasons, a proxy for economic insecurity. In both cases, another separate regression is performed interacting the platform work dummy with the year 2021, which is the year in which the second survey was administered. Two similar exercises are performed substituting the platform work dummy with platform work tasks. Thirdly, the platform work dummy is interacted with a measure of hours worked.

Results indicate that platform work is associated with lower incomes and with higher economic insecurity. After the Covid pandemic, the nature of platform work does not seem to have changed, as no differential effect is apparent in the relationship between platform work when interacted with the post-Covid year. While the impact is negative across the board, platform tasks exhibit a difference in the magnitude of their impact on economic conditions. Finally, platform workers appear to have lower household incomes and higher economic insecurity than their counterparts when they work less hours, and do not seem to reap the benefits of working overtime.

Hence, the third chapter serves both as an update on platform workers' economic condition and as a final assessment of the impact platforms have on work, confirming the tendencies hypothesised and documented in the first and second chapter with direct evidence of the heightened economic insecurity.

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The three essays in this thesis outline and confirm the main characteristics of labour in the platform economy, as they have been described in the theoretical framework outlined.

Enhanced flexibility coupled with the increased centralisation of market power and value creation results in negative outcomes for workers. Income earners (firms and workers alike) facing platform logics witness the decrease of their incomes and spaces of autonomy, in favour of purported increases in productivity and opportunity, on the one hand, but also of control and uncertainty, on the other.

Therefore, this thesis offers an empirical assessment of labour conditions in the platform economy that deviates from the neutral/optimistic one prevalent at the beginning of the rise of platforms (Sundararajan, 2016). It does so by making use of new data sources and methods, and by expanding the conceptualisation of platforms' influence on work to include the platform's competitors, suppliers, and vendors.

Platforms arise as the central economic power of the last twenty years, characterised by techno-organisational paradigms that lead to increasing concentration of control in the hands of few, large players, at the expense of worker well-being.

Chapter 1

How Amazon Shapes Local Labour Markets

As the Introduction has broadly outlined, large digital platforms derive substantial market power from their intermediation role and techno-organisational affordances, enabling them to exert both direct and indirect effects on the wider economy and to control critical infrastructures (Coveri et al., 2022; Rahman and Thelen, 2019). While platforms can enhance value creation and productivity, they may also reinforce trends toward job precarity and lower-quality employment, contributing to structural changes in labour markets and the organisation of work (Kenney et al., 2019; Garcia Calvo et al., 2023).

The presence of a digital platform can have four distinct effects on workers (Table 1). In particular, this chapter relates to substitution: digital platforms often replace traditional intermediaries by internalizing/externalizing functions and resources, typically relying on different types of workers or tasks than those displaced (Srnicek, 2017). At the same time, platforms expand economic activity by creating larger, more integrated markets for goods and services, generating jobs (Sundararajan, 2016). Monopsony power is however a moderating factor: as a central hub in these markets, the platform consolidates economic transactions. With significant power in both product and labour markets, it can exert downward pressure on wages for the workers it directly employs (Kumar, 2020). Wage compression can also arise as a consequence of routinary tasks becoming more standardised and automatable, a feature that large digital platforms exhibit as a result of their reliance on algorithmic management and digital monitoring technologies (Gonzalez Vàzquez et al., 2025).

E-commerce platforms offer a valuable context for examining the effects of digital platforms on labour markets. The goods they sell or intermediate are also available in brick-and-mortar and chain retail stores, meaning their entry introduces a competitive shock that can displace or reshape employment in traditional retail. At the same time, to fulfill orders, these platforms directly or indirectly generate employment in logistics and transportation, increasing labour demand in those sectors. Despite a growing literature on platform labour and logistics, empirical evidence on the spatial impacts of e-commerce platforms at a fine geographical scale remains limited. Qualitative studies have extensively examined working conditions at Amazon and in the broader logistics sector, often highlighting relatively low levels of employment protection and increasing labour flexibilisation (Bonacich and Wilson, 2011; Benvegnù et al., 2018; Delfanti, 2021b; Cirillo et al., 2025b). However, only a small number of studies provide quantitative evidence on how e-commerce reshapes local labour markets and regional economic structures (Chava et al., 2024). As a result, the geographically contingent effects of e-commerce on wages, employment, and income distribution remain underexplored. This omission is notable given that e-commerce may produce both localised and spatially uneven labour market outcomes. While brick-and-mortar retail establishments—particularly smaller ones—must locate close to consumer demand, logistics facilities such as warehouses face fewer spatial constraints (Fried and Goodchild, 2023). The expansion of e-commerce therefore implies not only sectoral shifts in employment, but also a partial redistribution of jobs from urban centres to peripheral or suburban areas (Chun et al., 2023).

From a labour market perspective, the redistribution associated with e-commerce extends beyond geography to encompass shifts between and within income classes. Lower-income earners may gain access to new employment opportunities in warehousing and logistics, provided that wages in these sectors exceed their outside options. At the same time, the expansion of e-commerce often leads to a decline in traditional retail employment—where many lower-wage jobs are concentrated—potentially exerting downward pressure on wages in that segment. Shop owners, earning higher incomes, may see their opportunities reduce. Further, as markets expand and reconfigure around platform-based models, workers — frequently self-employed or employed by small firms — face growing competition from new entrants and reduced price–cost margins, contributing to wage suppression. Given these contrasting dynamics, the net effect of e-commerce platforms on local labour markets remains, ultimately, an empirical question.

Against this background, this chapter estimates the net local impact of the entry of a major e-commerce platform—Amazon—on wages, employment, and income distribution across different levels of earners in Italy, using fine-grained municipal-level data. Amazon.com Inc., through Amazon Italian Logistics S.r.l., manages all Fulfillment Centers (FCs) established in Italy, making it a key actor in the country's e-commerce and logistics landscape. Focusing on local labour market areas, the analysis examines how the opening of Amazon facilities reshapes economic outcomes across municipalities and income groups.

To this end, a unique dataset was constructed by merging two primary sources. First, a list of Amazon facilities—including their locations and quarter of establishment—was obtained from MWPVL.com and cross-validated using newspaper reports of facility openings (Bauer and Fernández Guerrico, 2023; Chava et al., 2024). Facilities are classified into Fulfillment Centers (FCs)—large logistics hubs typically located in peripheral areas—and Delivery Stations (DSs)—smaller urban-oriented facilities designed to enable rapid delivery (Fried and Goodchild, 2023). Second, municipal-level data from personal income tax filings, maintained by the Italian Ministry of Economy and Finance, provide annual information from 2013 to 2023 on wages, employment, and the distribution of taxpayers across income brackets.

Using a difference-in-differences framework with staggered adoption and not-yet-treated controls, the analysis reveals that, on average, the opening of a new e-commerce facility has a negative effect on log per-capita wages in any given year-municipality. The dynamic effect intensifies over time: four years post-opening, per-capita wages in treated municipalities are 0.015 log points lower, corresponding to annual losses around 300p€er capita.

However, the analysis also reveals that the impacts of e-commerce vary between urban and peripheral facilities. More specifically, the establishment of a new Fulfillment Center is less strongly associated with declines in overall wages. In contrast, urban Delivery Stations appear to drive the long-term negative effects of e-commerce, with both wages and employment decreasing in these areas. This difference can be explained by the distinct characteristics of the two facility types. Fulfillment Centers are typically located farther from cities, in commuting zones where location decisions are influenced less by population density or income levels and more by factors such as access to a suitable labour pool and proximity to major highways. These are large facilities, employing between 800 and 1,200 workers. Conversely, urban Delivery Stations are smaller and employ fewer workers. They serve to enable rapid delivery in premium urban areas, where competition with an already abundant retail sector is more pronounced.

Focusing on income distribution, the empirical analysis reveals that municipalities hosting Fulfillment Centers experience an increase in the number of low-wage earners—taxpayers in the 0–26,000 euro bracket—although their incomes tend to decline. Conversely, among the highest earners—those in the 55,000+ euro bracket—urban area municipalities exhibit a reduction in the number of taxpayers, with significant change observed in average income within this group. For the middle-income bracket (26,000–55,000) €, changes in the number of taxpayers are smaller, yet significant.[1] Overall, the main analysis indicates that e-commerce is associated with no increases in employment and declines in wages. These effects are particularly pronounced in municipalities near urban areas, especially those hosting Delivery Stations. In contrast, the impact of labour market power—which is expected to be stronger in more dispersed and less elastic labour markets, such as those surrounding Fulfillment Centers—is evident in the lower incomes enjoyed by 0-26k earners.

Two main robustness checks have been performed to validate these findings. For instance, given that the definition of commuting zones by ISTAT may not perfectly capture the municipalities affected by a facility's presence, an alternative analysis was conducted considering municipalities within a 50 km radius from the centroid of the municipality hosting the e-commerce facility as treated. The results remain qualitatively unchanged, providing reassurance about the accuracy of the empirical strategy. Additionally, since the Milan commuting zone is classified as a Fulfillment Center and might potentially bias the estimates, regressions were re-run excluding this zone. No substantive changes were detected, confirming that this labour market area was not driving the results.

The remainder of this chapter proceeds as follows. Section 1.1 reviews the main contributions on e-commerce and related fields stating our research questions. Section 1.2 details the data sources and outlines the methodology. Results are presented in Section 1.3, and Section 1.4 offers discussion and concluding remarks.

1.1 Setting the scene: literature review and research questions

Going beyond analyses purely focused on platform work in a particular sector, the present article represents the first study attempting to establish a direct relationship between (e-commerce) platform development and general, non-sectoral variations in wages and employment within EU local labour markets. It interprets the presence of a platform not as a circumscribed phenomenon within

[1] Income brackets provided by the Ministry of Economy and Finance, reflecting Italy's progressive tax rates, are as follows: below 0, 0–10,000 , € 10–15,000 , € 15–26,000, € 26–55,000, € 55–75,000, € 75–120,000, € and over 120,000. € Due to likely misreporting, the lowest and highest brackets are excluded, and the first three and last two brackets are aggregated, resulting in the 0–26, 26–55, and 55–120 brackets used here.

a specific segment of the labour market, but as a paradigm shift in the form of organisation of work and of the economy as a whole. As such, it also contributes to the literature on the economic effects of e-commerce on market structure and industry dynamics, and more generally on labour outcomes associated with digital technologies.

Digital platforms are connected infrastructures, providing a space for interaction between different agents, as well as an algorithmic governance structure for coordinating these interactions. Taking advantage of strong network effects, they occupy a central position in the markets they orchestrate, allowing them to extract significant rents from the power structure resulting from their intermediation activities (Urzì Brancati et al., 2019; Belleflamme and Peitz, 2021; Kenney and Zysman, 2016; Srnicek, 2017). Digital platforms, and e-commerce chiefly among them, reduce different types of costs for their participants – particularly search costs (Acs et al., 2021; Goldfarb and Tucker, 2019). As information about prices and product quality becomes *prima facie* easily comparable for online consumers, the price of homogenous goods decreases, leading to reduced price dispersion in online markets, while heterogeneous goods compete on quality, as measured by reviews and ratings (Brynjolfsson and Smith, 2000; Brynjolfsson et al., 2010; Ghose et al., 2006; Ghose and Yao, 2011; Goldmanis et al., 2010; Dolfen et al., 2023). The presence of a digital platform, however, is not neutral in terms of the market restructuring it imposes on the new or existing industries where it establishes its presence. Platform markets exhibit strong tendencies towards concentration, associated with self-preferencing, tying, and other anticompetitive practices (Farronato and Fradkin, 2018; Waldfogel, 2024; Khan, 2016). At the same time, platform power is mediated by the local/global nature of the platform's economic activity. Platforms embedded in a local context are shown to have little negative impacts on labour outcomes and to exert limited power over their participants (An and Chung, 2025). Global platforms instead may affect the distribution of gains by introducing new sources of tension- such as competition with foreign products, or job creation away from existing retail labour markets (Forman et al., 2009; Brynjolfsson et al., 2009; Forman et al., 2012). Labour outcomes in connection with the rise of platforms are heterogeneous both in terms of geography, as outlined above, and in terms of industry. E-commerce tends to create employment primarily in logistics and transportation, while contributing to job losses in the retail sector. Similarly, wages rise for workers in industries complementary with the digital platform, and fall for those industries entering in competition with it (Chava et al., 2024; Bauer and Fernández Guerrico, 2023). Notwithstanding sectoral and geographical differences, the introduction of new digital technologies is almost always associated with productivity increases, alongside polarisation between workers between low-skilled/de-skilled labour and high expertise hires in specific segments and geographies (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2020). Platforms - the organisational and economic entity most associated with digital technologies - exhibit similar effects, subject to workers' skill levels, employment contract stability, and the focus of technological change (Cirillo et al., 2021, 2025a).

Amazon is one of the largest digital platforms in the world. It controls a large e-commerce marketplace, cloud computing facilities with impressive market shares, and a highly-developed transnational logistics network (Massimo, 2024; Coveri et al., 2022). The platform appears to have had a distinctive impact on workers in terms of working conditions, application of technological innovations, and more generally on the labour process (Massimo, 2024; Cirillo et al., 2025b). Amazon has also affected vendor firms on its marketplace and their workers, and workers of displaced brick-and-mortar businesses (Khan, 2016; Zhu and Liu, 2018; Chava et al., 2024). As a digital platform, Amazon is able to leverage its data advantage to optimise its logistics, increase the pace of work, and exert enhanced control towards its associates- workers, subcontracting firms, and vendors alike (Delfanti, 2021b; Coveri et al., 2022). Specific studies have focused on working conditions at Amazon and more generally on its impact on work. Amazon has often been at the centre of attention for the intensity associated with working within its logistics supply chain, often resulting in injuries for workers and more generally in economic insecurity (Benvegnù et al., 2018; Gutelius and Theodore, 2019; Delfanti, 2021b). Examined in its totality, the company appears to be constantly pursuing strategies of value appropriation, resulting in firm closures and job losses (Khan, 2016; Zhu and Liu, 2018), also through the use of robots to diminish the relative importance of human labour (Delfanti, 2021a; Cirillo et al., 2025b). The impact Amazon has is therefore novel concerning the multifaceted pervasiveness of its presence in different product/labour markets, making it a worthwhile object of study across disciplines and subjects in economics, geography and sociology (Alimahomed-Wilson and Reese, 2020; Vallas et al., 2022; Bauer and Fernández Guerrico, 2023; Cirillo et al., 2025b; Delfanti, 2021a; Hardaker, 2024).

The nature of Amazon as an e-commerce platform demands situating the analysis also in the longer history of disruptions in retail. Its impacts mirror, with different scale and implications, those brought upon retail employment, small businesses, and communities by large retailers, such as Walmart or IKEA (Mihaescu et al., 2024; Holmes, 2011; Wiltshire, 2021).[2] Chava et al. (2024) situate Amazon within the broader stream of retail disruptions and upheavals. Their paper estimates losses in retail employment and wages outweighing gains from logistics and transportation employment in the United States.

Disruption patterns involve entire sectors and economies. Yet, it has long been understood that the local dimension of disruption reveals also urban/rural heterogeneities, or deepens existing ones. Two separate studies, Chun et al. (2023) and Choe et al. (2024), analyse the impact of e-commerce in South Korea: they find sustained declines in retail employment in non-metro areas, where e-commerce leads directly to firm closure. In urban contexts, retail workers find employment, but their wages decline. However, the spatial/economic distributive implications of digital platform expansion, more generally, and of e-commerce development, in particular, have not been explored. Almost no study (Biagi and Falk (2017) representing the only exception) focuses on impacts on the general labour force at the local level, and no study is able to observe punctual variations in the distribution of income as a result of the reshaping of the labour/product markets operated by platforms.

This chapter focuses on a single country — Italy — where digital platforms have played a significant role in reorganising productive factors and value chains across industries such as retail, restaurants, and hospitality (Guarascio and Sacchi, 2018; Cirillo et al., 2025a). It does so including a urban/rural dimension, akin to Choe et al. (2024), while expanding the focus of the analysis from sector-specific wages towards the broader municipal-level labour force. In Italy Amazon employed, as of 2023, around 18,000 "associates" (full-time workers), and claimed to be generating around 100,000 jobs- of which 60,000 through its third-party sellers.[3] The starting gross wage followed the

[2] In the case of IKEA, however, the net effects on Swedish labour markets appear to have been largely positive in terms of wages and employment, probably due to complementarities with new and existing retail establishments (Daunfeldt et al., 2017).

[3] Lorenzo Barbo (Amazon Logistics Italia S.r.l.), About Amazon, https://tinyurl.com/barbo2023.

fourth level of the union-negotiated logistics national contract, for an amount of 1.675,69 i €n 2023, which can be considered a competitive salary in the Italian wage structure.[4] However, Amazon also employs temporary workers and turnover among its full-time workers is widespread: most workers may work less hours than otherwise usual, and full-time workers are on the other hand often overworked, leading to dismissal or voluntary resignation whenever certain company standards are not met (Massimo, 2024; Delfanti, 2021b). The logistics of Amazon, and of e-commerce more in general, have evolved into a two-tiered system: large, labour-intensive warehouses, named Fulfillment Centers, receive goods from ports and airports and are located in rural areas, a locational pattern shaped by factors such as lower land costs, proximity to major highways, and the availability of cheaper, lower-skilled labour (Rodrigue, 2020; Risberg, 2023; Fried and Goodchild, 2023; Kang, 2020; Cattero and D'Onofrio, 2018). Smaller facilities – Delivery Stations – are responsible for the final distribution to consumers; they are located closer to urban centres, enabling same-day and two-day shipping.[5] Therefore, where a Delivery Station is present, Amazon enters more strongly into competition with brick-and-mortar retailers, also because of the increased competitiveness of its Prime offers (Chava et al., 2024).[6] A third type of Center, the Sortation Center, is also part of Amazon's logistics system in Italy. The two Sortation Centers can be also regarded as facilities primarily hiring logistics workers outside of major urban hubs. From a geographical perspective, Figure 1.1 shows that Fulfillment Centers and Sortation Centers tend to be based in the North, and in municipalities located in labour market areas farther away from main cities. Instead, Delivery Stations signal Amazon presence for fast shipping near almost all cities over 100.000 inhabitants.[7]

One result of this increased competition with retail, but also with producers, has been the documented decrease in independent shopkeepers and owners (Cirillo et al., 2024b; Choe et al., 2024). At the same time, rural areas witness an inflow of low-income workers, often only temporarily employed at Amazon warehouses and sometimes constituting a racialised workforce (Tapia et al., 2024; Zanoni and Miszczyński, 2024).[8] Therefore, the spatial element is also distributional in its effects: the platform alters the income structure of the places in which it embeds itself, increasing the number of low-income earners – and likely benefitting from their availability (Cattero and D'Onofrio, 2018) – in rural areas while provoking a decrease in high-income business owners in cities and towns.

The spatial divides, and the distributional consequences associated with them, lead to the formulation of two research questions related to the local dynamics of wages, employment, and the income distribution after the arrival of an e-commerce platform.

RQ1: *What is the impact of the opening of a new Amazon facility on municipal-level wages and employment? To what extent do these effects differ between Fulfillment Centers and Delivery Stations?*

RQ2: *How does the opening of a new Amazon facility affect the number of earners and average wages*

[4]The collective contract is available at the following link: https://tinyurl.com/ccnl2023amazon.

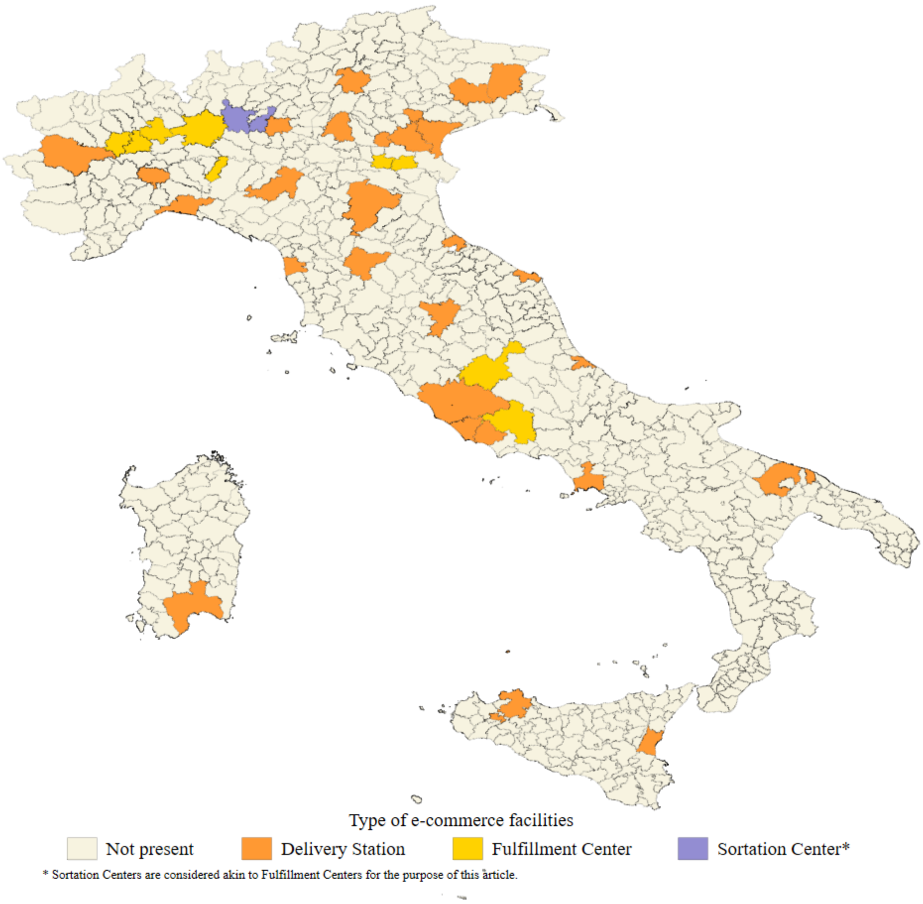
[5]For an overview, Amazon's own website lists the types of facilities: https://tinyurl.com/fcds2023amazon.

[6]Figures A.1 and A.2 in the Appendix provide an overview of the relationship between population density, highway proximity, and degree of urbanisation.

[7]Main exceptions are Salerno, Foggia, Taranto, Reggio Calabria, Messina, and Sassari, all located in the South and Islands.

[8]A clear example of this behaviour is also present in the Oscar-winning motion picture Nomadland (Chloe Zhao, 2020), where the viewer follows a "travelling workforce" operating as pickers in an Amazon warehouse during peak season, in the United States, among other jobs.

Figure 1.1: Type of Amazon platform facilities



across different income levels? Are these effects consistent along the wage distribution, or do they differ between low-, middle-, and high-income earners?

To answer them, we turn to two main econometric exercises.

1.2 Data and empirical strategy

1.2.1 Data

To examine the impact of e-commerce on wages and employment, we build a novel municipality-level dataset that combines detailed information on the opening of new Amazon facilities with key labour market indicators. More in detail, to proxy the rise in e-commerce activity in Italy, we compile a comprehensive list of Amazon's logistics centres—the country's dominant e-commerce operator—sourced from a logistics consulting firm.

This publicly available data has previously been used in studies focused on the United States (Chava et al., 2024; Bauer and Fernández Guerrico, 2023). We validate each entry through cross-referencing with local newspaper reports that typically announce new warehouse openings in conjunction with expected job creation. Between 2011 and 2023, Amazon opened 57 such facilities across Italian municipalities.

We exclude the first opening, as it falls outside the scope of our data. We further exclude facilities opened within already treated LMAs, as these do not introduce new treated municipalities. Facilities inaugurated in 2023 are also dropped, given the absence of a post-treatment period with the available data.

Amazon facilities can be Fulfillment Centers or Delivery Stations, with different characteristics. Delivery Stations are closer to cities, enabling fast shipping; Fulfillment Centers are mostly used for bulk logistics operations, are closer to highways (see Figure A.1 in the Appendix) and removed from cities to compress land and labour input costs. A third type of Center, the Sortation Center, is also present. We classify Sortation Centers as Fulfillment Centers, given their similar functions and characteristics.

Our final sample comprises 37 facility openings across distinct commuting zones over the 2015–2022 period.[9]

We then link these facility openings at the municipal level to income tax data from the Italian Ministry of Economy and Finance, which provide annual information on total labour income (gross wages) and the number of wage earners (employees) in each Italian municipality for the period 2013–2023. Wages are defined as income earned from subordinate employment, while the number of employees defines employment itself. Disposable income deriving from a multiplicity of sources is instead the basis for the definition of taxable income brackets.

Treatment is assigned at the Labour Market Area [10] level, as the proximity of a new facility

[9] To account for potential anticipation effects, we treat facilities opened in the third quarter of a given year as opening in the following calendar year.

[10] Eurostat – European Harmonised Labour Market Areas: Methodology on Functional Geographies with Potential, 2020 edition, `https://ec.europa.eu/eurostat/web/products-statistical-working-papers/-/ks-tc-20-002` . An LMA is defined as a functional area in which at least 80% of the employed population commutes within the boundaries of its constituent municipalities.

is expected not only to generate local employment opportunities for the municipality but also to enhance delivery efficiency by reducing shipping times, thereby affecting local labour markets more broadly (Chava et al., 2024).

Table 1.1: Descriptive statistics for municipalities, 2013

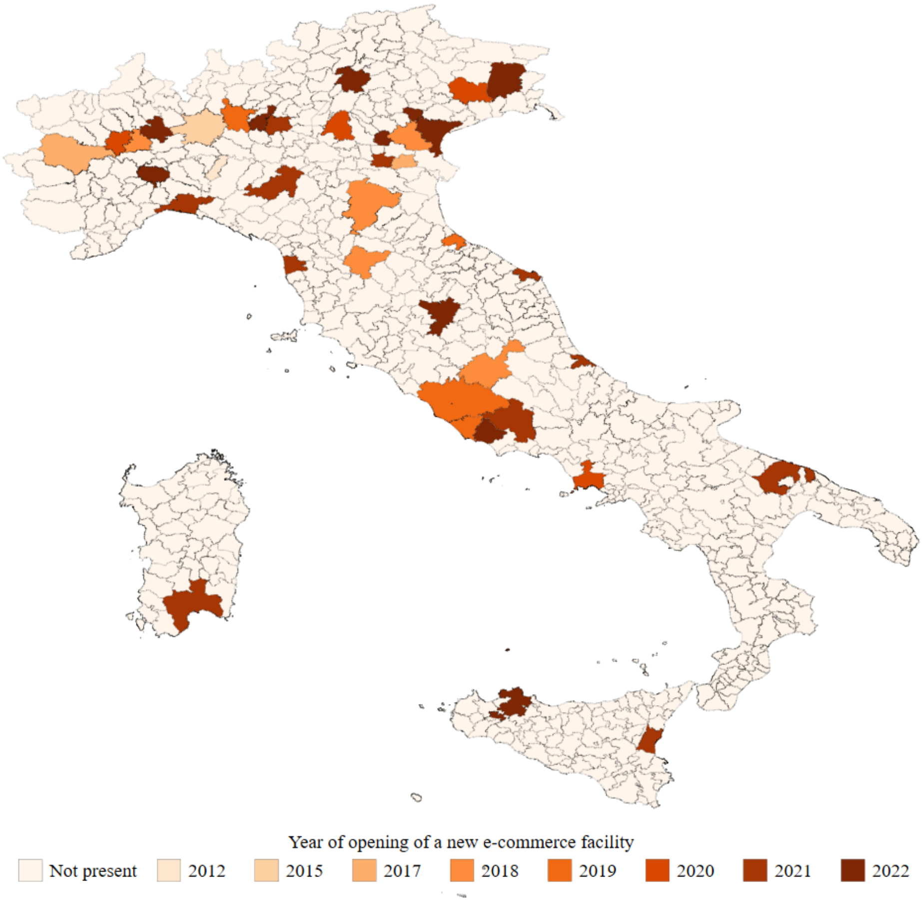
	Not present	Fulfillment Center	Delivery Stations	Total
Number of municipalities	6,661 (82.8%)	552 (6.9%)	832 (10.3%)	8,045 (100.0%)
Employees in municipality	1813 (4162)	3962 (21452)	7430 (39125)	2541 (14389)
Per capita wages	18145 (3603)	21639 (3822)	20387 (3091)	18616 (3724)
Number of income earners under 26,000 €	2890 (6117)	5113 (25840)	10373 (50759)	3817 (18659)
Per capita income for the 0-26k income bracket	12061 (1746)	13647 (1162)	12975 (1263)	12265 (1732)
Number of income earners between 26,000 a€nd 55,000 €	631 (1744)	1771 (10657)	3163 (19402)	971 (7059)
Per capita income for the 26-55k income bracket	33369 (1807)	33960 (958)	33831 (864)	33457 (1697)
Number of income earners over 55,000 €	112 (388)	471 (4689)	754 (6111)	203 (2352)
Per capita income for the 55-120k income bracket	70893 (36658)	82578 (25188)	82231 (21528)	72867 (34967)

As Table 1.1 shows, municipalities that host an Amazon facility differ systematically from those that do not. On average, they have a larger number of employees and higher per-capita wages. The shares of both low- and high-income earners are also higher, while the number of middle-income earners does not differ significantly [11].

Figure 1.2 depicts the temporal and spatial evolution of Amazon's expansion across Italy. The platform initially concentrated its growth in the North and in the area surrounding the capital, Rome, before extending its network—primarily via Delivery Stations—to major cities in the Centre and South. These spatial and temporal heterogeneities are explicitly accounted for in the empirical analysis through the identification strategies and controls employed as I will detail in the next subsection.

[11] Table A.1 in the Appendix reports descriptive statistics excluding Milan. Removing Milan reveals additional heterogeneities: municipalities hosting a Fulfillment Center appear more similar to non-treated municipalities, except in terms of per-capita wages, which remain persistently higher. These patterns reflect Amazon's strategy of locating Fulfillment Centers near peripheral municipalities, yet predominantly within the wealthier North of Italy, where approximately 46% of the national population resides.

Figure 1.2: Development over time of Amazon platform facilities



1.2.2 Methodology

In order to estimate the impact of a new e-commerce facility on local per-capita wages and on the local number of employees, we apply an event-study approach (Callaway and Sant'Anna, 2021).

This strategy entails aggregating the results of separate difference-in-differences regressions, estimating the impact of each facility (event) on a given territory, in a given year. During aggregation, the effects of estimating the impact in different years and for different units (municipalities) are meted out, allowing the retrieval of the dynamic impact over time of a new Amazon facility, as well as the static year-time effect (the overall measure, shown in Tables 1.2 and 1.3).

The control municipalities, for which the event did not occur, may have unobservable characteristics correlated with the choice of Amazon not to locate there. Thus, not-yet-treated municipalities are used as controls. These are municipalities scheduled to receive a facility in future periods but untreated in the year corresponding to the estimated treatment cohort. Employing not-yet-treated municipalities as controls helps mitigate concerns related to spatial correlation and potential self-selection bias, as the e-commerce platform does not choose its locations randomly (see Figures A.2 and 1.1 in the Appendix).

We estimate the following equation:

$$ATT_{c,t} = \alpha + \beta PostAmazon_{c,t\geq g} + \Phi_c + \Theta_t + \epsilon_{c,t} \tag{1.1}$$

where $ATT_{c,t}$ denotes the average treatment effect on the treated for the outcome variables in municipality c in year t; $PostAmazon$ is a binary indicator equal to 1 if the municipality belongs to an LMA where an e-commerce facility is present in year $t \geq g$, with g indicating the year of the facility's opening; Φ_c represents municipality-fixed effects; Θ captures time fixed effects; and ϵ represents doubly robust inverse-probability-weighted errors, computed using a wild bootstrap procedure (Rios-Avila et al., 2021).

In order to reply to *RQ1* and *RQ2*, equation 1.1 has six different outcomes, estimated across three different reference populations.

To answer *RQ1*, we regress the log of the wage and the log of the number of income earners. This is done first with the full sample of Amazon facilities, and then splitting the sample between municipalities impacted by a Fulfillment Center and those impacted by a Delivery Station.

To address *RQ2*, we regress first the log of the number of income earners in the three brackets we have identified, first jointly and separately thereafter. We then regress the log of the average income in each income bracket, in the same manner.

Additionally, although recent research suggests that zones of consumption are smaller than commuting zones (Batch et al., 2025), partly alleviating concerns related to treatment misclassification, LMAs may still imperfectly capture the true area of impact of e-commerce expansion.

To address this, we conduct a robustness check in which treatment is redefined based on geographic proximity: for both urban (Delivery Station) and peripheral (Fulfillment Center) areas, we consider as treated all municipalities located within 50 kilometers of the municipality hosting the facility.[12]

Lastly, given that Milan —Italy's most urbanized LMA— is classified as hosting a Fulfillment Center, we repeat the analysis excluding this event to test the sensitivity of our results.

1.3 Results

The average impact of new e-commerce facilities on wages appears to be negative. The effect is driven by municipalities in which a Delivery Station is present, while the impact of Amazon is neutral for Fulfillment Centers. Interestingly, no positive impact can be detected on the number of employees.

Table 1.2: Impact of a new Amazon facility on log wages

	(1) All warehouses	(2) Fulfillment Center	(3) Delivery Station
ATT	-0.0048954***	-0.0037991	-0.0091444***
	(0.001424)	(0.0029484)	(0.0016744)
N	14,889	6,072	8,817

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

More specifically, the baseline estimates indicate a decrease of 0.004 log points in the average wage in the static aggregation, across years and municipalities. When examining the impact dynamically, the effect appears to grow over time. By the fourth year following the establishment of

[12] Distances are calculated using the geographic centroids of municipalities. Specifically, treatment is assigned based on whether the centroid of a given municipality falls within a 50-kilometer radius of the centroid of the municipality where the facility is located.

Table 1.3: Impact of a new Amazon facility on the log number of employees

	(1) All warehouses	(2) Fulfillment Center	(3) Delivery Station
ATT	-0.00014996	-0.002011	-0.00009
	(0.0017140)	(0.003019)	(0.002382)
N	14,889	6,072	8,817

Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the facility, the average wage in treated municipalities declines by more than 0.015 log points. In municipalities hosting a Delivery Station, the decline is twice as large (see Figure 1.3).

Taking stock of this evidence, we can assess that a new Amazon facility decreases wages, particularly when located within a urban area. At the same time, the impact that the platform has on employment is unclear.

Figure 1.3: Impact of a new Amazon facility on wages

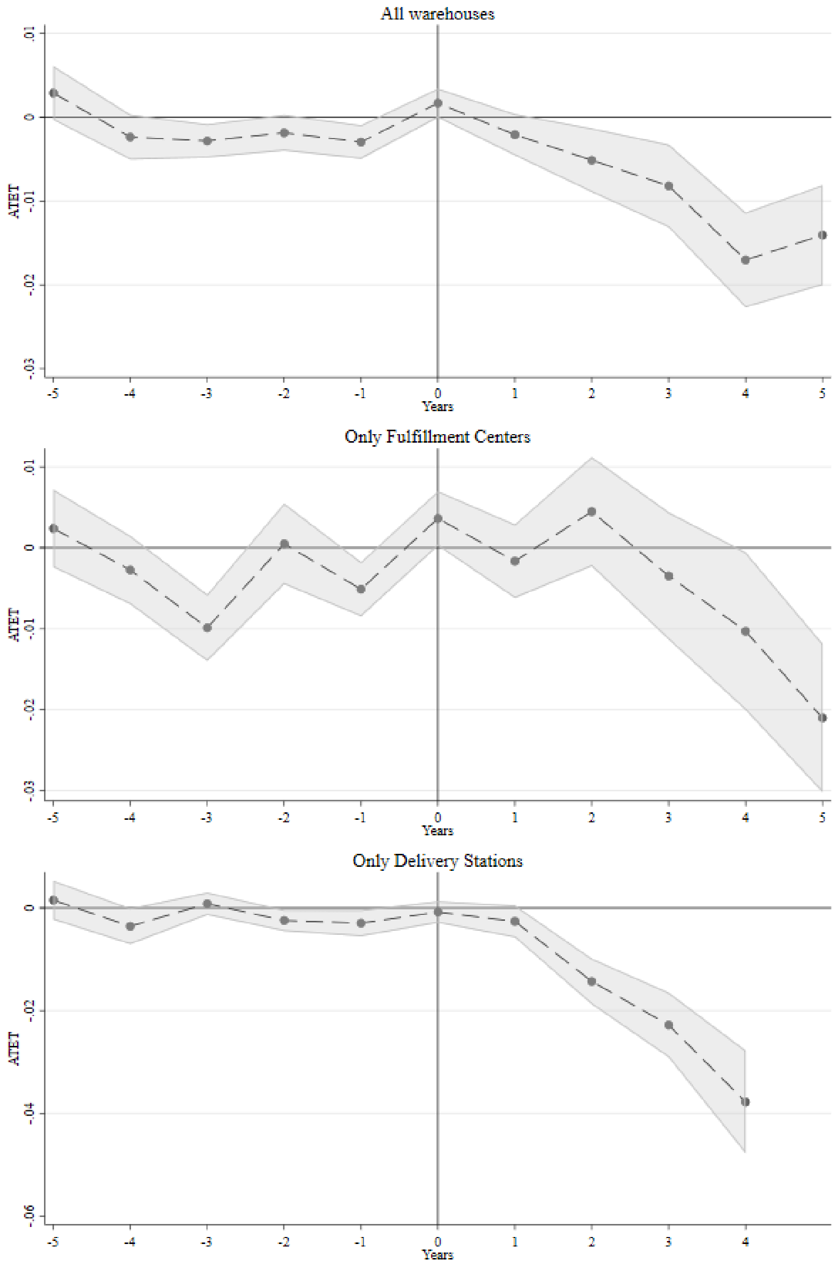
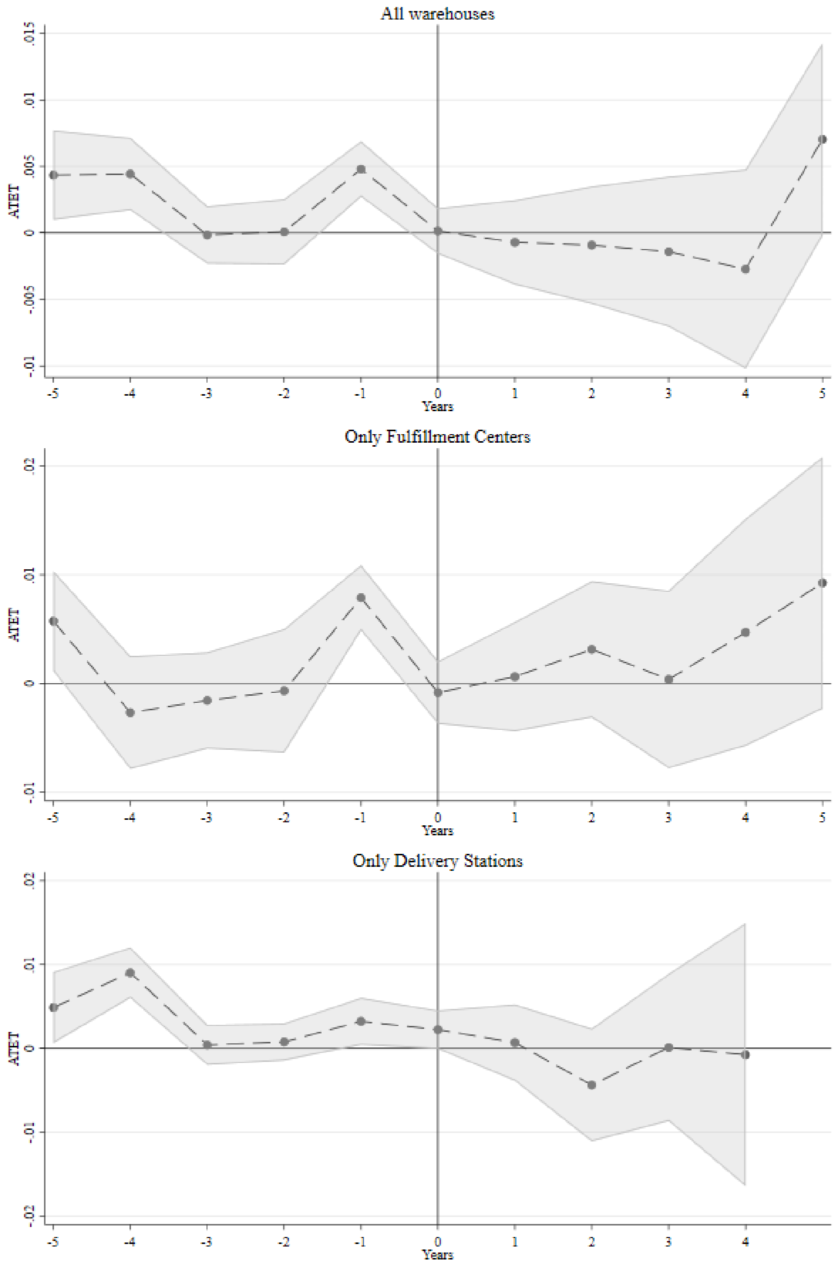


Figure 1.4: Impact of a new Amazon facility on number of employees



Focusing on *RQ2*, Table 1.4 shows that the number of income earners in the lowest bracket (0–26,000) increases in municipalities where a Fulfillment Center has opened. The opposite trend is observed across higher income brackets. Notably, the highest income bracket — those earning above 55,000 € shows the most significant decline. Concerning the impact on average income by bracket (Table 1.5), results indicate that the income level of the lowest bracket decreases, with stronger impact for Fulfillment Center municipalities. The level of higher-income brackets decreases mostly close to Delivery Stations, instead.

Table 1.4: Impact of a new Amazon facility on number of earners by income bracket

	Log of the number of income earners under 26,000 €		
	(1)	(2)	(3)
	All warehouses	Fulfillment Center	Delivery Station
ATT	0.006313***	0.012374***	0.0043*
	(0.001436)	(0.002619)	(0.001674)
N	14,889	6,072	8,817
	Log of the number of income earners between 26,000 and 55,000 €		
	(1)	(2)	(3)
	All warehouses	Fulfillment Center	Delivery Station
ATT	-0.01838***	-0.02657121***	-0.0173389***
	(0.0024388)	(0.004841)	(0.0027201)
N	14,888	6,071	8,817
	Log of the number of income earners over 55,000 €		
	(1)	(2)	(3)
	All warehouses	Fulfillment Center	Delivery Station
ATT	-0.02567***	-0.035452***	-0.022887***
	(0.005092)	(0.0096)	(0.006577)
N	14,131	5,689	8,442

Robust standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Variations in N are due to missing data on some income brackets in certain municipalities.

Table 1.5: Impact of a new Amazon facility on average income by income brackets

	Log income under 26,000 €		
	(1)	(2)	(3)
	All warehouses	Fulfillment Center	Delivery Station
ATT	-0.0062619***	-0.0085253***	-0.004432***
	(0.0009379)	(0.00163)	(0.001185)
N	14,889	6,072	8,817
	Log income between 26,000 and 55,000 €		
	(1)	(2)	(3)
	All warehouses	Fulfillment Center	Delivery Station
ATT	-0.00084267*	-0.0016474	-0.001414**
	(0.0004219)	(0.0008578)	(0.0005087)
N	14,888	6,071	8,817
	Log income over 55,000 €		
	(1)	(2)	(3)
	All warehouses	Fulfillment Center	Delivery Station
ATT	-0.0056832	-0.0009738	-0.00881*
	(0.003943)	(0.009479)	(0.004361)
N	14,131	5,689	8,442

Robust standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Variations in N are due to missing data on some income brackets in certain municipalities.

In light of the results, we can assess that Amazon has compressed the income distribution by reducing relatively more the number of income earners in the higher brackets (see also Figures 1.5 and 1.6 in the Appendix), while increasing the number of low income earners. The effect is more pronounced close to Fulfillment Centers, which exhibit also the largest decreases in the income level of this group. This can be interpreted as a sign of monopsony power on the part of the platform, which increases employment opportunities for low income earners, but does not foster wage growth.

Figure 1.5: Impact of new e-commerce facilities on number of earners by income brackets

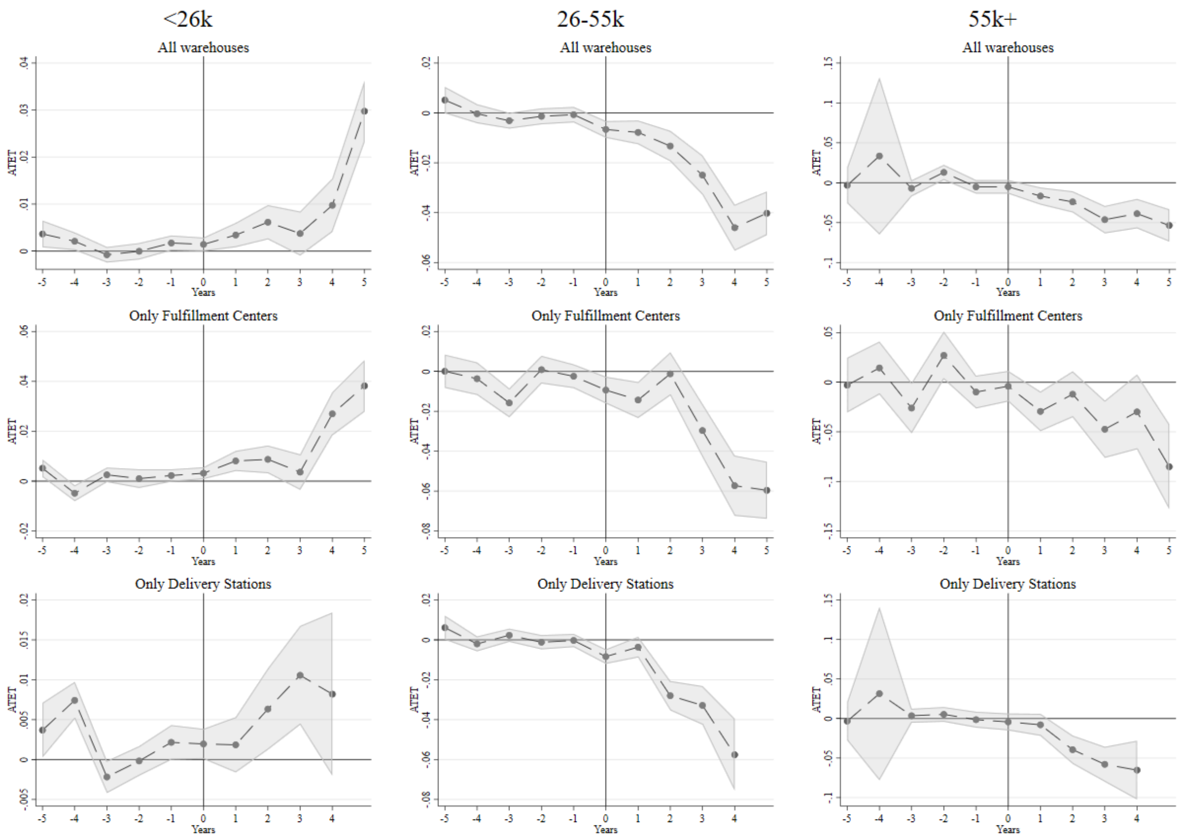
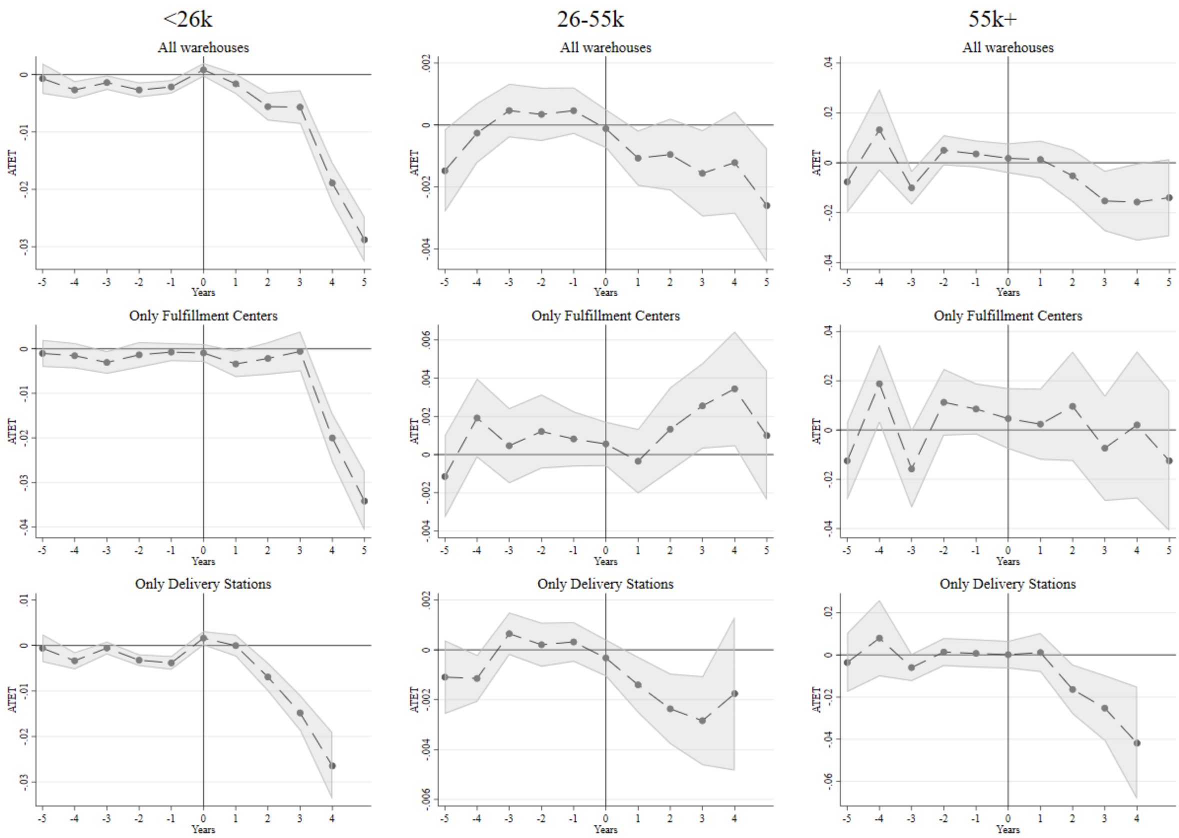


Figure 1.6: Impact of new e-commerce facilities on average income by income brackets



1.3.1 Robustness checks

As anticipated in Section 1.2, consumption zones may differ from commuting zones. Therefore, as a robustness check, we estimate the impact of the opening of a new e-commerce facility using an alternative method to identify treated areas. Specifically, we define treated zones as those within a 50 km radius of the centroid of the municipality where the facility was opened. This approach yields qualitatively similar results, reinforcing the validity of the choice of Local labour Market Areas (LMAs) to identify the treatment. A comparable outcome is obtained when the analysis is repeated excluding Milan as a Fulfillment Center (see Appendix).

The 50km radius treatment identification, combined with the use of not-yet-treated controls, relies on less observations than the LMA approach. Nonetheless, results indicate quite clearly that the magnitude and direction of the impacts hold. Dynamic effects (Figures A.3 and A.4 in the Appendix) resemble the impacts documented in the main analysis.

Removing Milan from the list of facilities does not qualitatively alter the results. The Milan Fulfillment Center is also the first one in our considered sample, thus reducing the pre-trend years in the aggregation from 5 to 4. Still no impact is detected concerning FCs, while the overall estimate on the log number of employees indicates a slightly lower loss (Figures A.5 and A.6 in the Appendix).

These results show that the impact does not depend from a single warehousing facility or geographical pattern, and it is only mildly sensitive to alternative identification strategies, further reassuring us of the estimates' validity.

1.4 Discussion and conclusion

This chapter provides the first evidence on the net impact of e-commerce on wages and employment in Italy. It leverages the staggered rollout of warehouses by the leading e-commerce platform in Italy—Amazon—to identify these effects. Consistent with prior research (Chava et al., 2024; Bauer and Fernández Guerrico, 2023; Chun et al., 2023), findings indicate that e-commerce has had a negative impact on labour markets.

Specifically, using an event study approach applied to a municipality-level dataset, results suggest that e-commerce platforms exert a negative local effect on wages. The impact is likely driven primarily by the substitution of existing jobs with lower-paying ones in urban areas. In fact, when focusing on the specific characteristics of e-commerce facilities, estimates reveal substantial heterogeneity. Delivery Stations, located closer to urban centres, drive the impact. As urban labour markets tend to host more establishments related to consumption, such as brick-and-mortar stores, the main effect at play appears to be one of substitution between online and offline sales. While detailed sector-level data on wages and employment are unavailable for each municipality or Local labour Market Area (LMA), it is reasonable to infer that e-commerce predominantly generates new jobs in logistics and transportation, while simultaneously competing with traditional brick-and-mortar retail stores (Chava et al., 2024; Chen and Tsai, 2023).

Municipalities close to Fulfillment Centers, instead, do not show significant impacts in terms of either wages or employment. In Fulfillment Centers, Amazon locates most logistics jobs. These are also located in less central hubs for retail demand. Yet, the implication would then be that, on average, the impact of Amazon should be one of job creation, which does not materialise.

As a digital platform, Amazon also has an impact in the long run, as it reconfigures around itself the demand for logistics services, driven by enhanced levels of concentration in the product markets where it is present. This results in some form of labour market power in municipalities with lower elasticity of labour supply, which provide less job opportunities outside the platform.

Evidence for this dynamic can be found in the decomposition of the impact across income brackets: lower income individuals increase in number; their wage decreases, signalling some form of labour market power at play. This pattern is particularly evident in municipalities close to a Fulfillment Center, where the number of low-income earners increases, while they experience the most significant income reductions in rural municipalities. This suggests that the platform's hiring practices and its control over demand play a role in driving these outcomes.

Meanwhile, the decline in the number of taxpayers in the highest-income bracket is larger than in the middle-income bracket, and more than four times larger than in the lowest-income bracket. Within their bracket and higher-income earners experience the most significant income reductions in urban municipalities.

Taking stock jointly of the evidence, it would appear that a digital platform – and particularly an e-commerce, dominant one such as Amazon – has distinctive local impacts on labour, interrogating the literature on the way in which technological change fosters organisational adjustments in markets (Autor et al., 2020; Autor, 2022; Johnson and Acemoglu, 2023). These may result in a redistribution of the underlying efficiency gains from the adoption of new firm structures and modes of production/consumption: despite the fact that a platform such as Amazon is able to obtain record revenues, little of these enhancements in productivity become apparent in the places in which it establishes operations.

Platform power produces new spatial and distributional divides. Its negative impacts are most felt in cities, where retail outlets have a new source of competition and manufacturers similarly suffer the inflow of goods from the e-commerce marketplace. Rural areas, on the other hand, witness systematic inflows of low-income earners, which are kept on earning levels below existing ones by effect of their decreased bargaining power vis-à-vis Amazon. A further proof of this dynamic is the structural weakness unions exhibit in mobilisation within the Amazon supply chain, also augmented by the algorithmic labour management practices of their counterpart (Lee et al., 2025; Massimo, 2024).

While this chapter offers a valuable contribution to the growing literature on e-commerce and digital platforms, several limitations must be acknowledged.

First, the analysis does not differentiate between sectors or types of employment, which constrains our ability to assess sector-specific effects. For instance, it cannot be disentangled whether job losses or wage changes are concentrated in retail, manufacturing, or other industries potentially affected by the expansion of e-commerce. This limits the granularity of the findings and their applicability to targeted labour market policies.

Second, the study does not include firm-level data, preventing the analysis of local business responses to the entry of large e-commerce platforms. Without firm-level information, it is impossible to explore changes in firm creation or closure rates, productivity shifts, or strategic responses by incumbents, such as investment in digital technologies or changes in employment practices. This limitation arises from the absence of representative firm-level data at the municipality level.

Third, while the paper accounts for spatial variation through the urban/rural divide, the analysis lacks a macro-regional perspective. Regional economic structures and labour market institutions differ significantly across the country, potentially mediating the effects of e-commerce in important ways. Incorporating this perspective could help reveal whether some regions are more resilient or more vulnerable to platform-driven economic changes.

Addressing these limitations is a promising area for future research. Access to administrative data would also allow for a more nuanced understanding of the mechanisms at play.

Two policy implications arise. Firstly, the opening of a platform facility, and more extensively platform presence in a local labour and product market, should be paired with measures aimed at compensating and/or protecting existing businesses and workers from disruption, in particular in urban contexts. Secondly, more stable employment gains should be secured from the platform's presence in rural areas, and the bargaining power of unions vis-à-vis the platform should be enhanced with rules aimed at assigning shared responsibility for employment, also of third-party subcontractors and vendors.

Some circumscribed evidence of mobilisation in contrast with the opening of new Amazon facilities is already available;[13] similarly, in a few Amazon establishments unions have started gaining ground. Recent disputes centred on the contractual conditions of externalised workers, who concentrate in last-mile delivery operations linked to Delivery Stations. The April 2025 nationwide strike

[13] `https://tinyurl.com/AmazonCasale`, `https://tinyurl.com/AmazonRoncade`.

of Amazon last-mile drivers, with a reported 85% adherence rate, focused explicitly on the value of travel allowances, year-on-year wage increments, and the regulation of workloads imposed through algorithmic management.[14] Localised disputes have also highlighted the wage erosion mechanisms operating through subcontracting chains, agency work, and the unilateral allocation of vehicle damage costs to drivers.[15]

However, local institutions have not yet begun to understand the impacts for the wider economic tissue of a new Amazon facility. National unions and shopkeeper associations, and local environmental groups and citizen committees are hardly cooperating, mainly because of a lack of immediate linkage between Amazon Delivery Station presence and sales decrease in surrounding areas – a gap that this chapter has aimed to close.

The union mobilisation, connected mainly with drivers and temporary workers, underlines how the disruptive potential of platforms is has a strong relationship with the power dynamics platforms impose on their subcontractors and other participants in their ecosystem. A platform disrupts the economic tissue around itself, and subsumes existing businesses by providing new sales venues, but also channels of dependency. This mechanism is at the core of the reasoning in the second chapter.

[14] `https://tinyurl.com/scioperoAmazon`.

[15] `https://tinyurl.com/AmazonColleferro`, `https://tinyurl.com/AmazonBologna`, `https://tinyurl.com/AmazonBrescia`.

Appendix for Chapter I

Tables

Table A.1: Descriptive statistics for municipalities - without Milan, 2013

	Not present	Fulfillment Center	Delivery Stations	Total
Number of municipalities	6,661 (84.6%)	378 (4.8%)	832 (10.6%)	7,871 (100.0%)
Employees in municipality	1813 (4162)	1905 (3728)	7430 (39125)	2411 (13414)
Per capita wages	18145 (3603)	20009 (2632)	20387 (3091)	18471 (3594)
Number of income earners under 26,000 €	2890 (6117)	2698 (4926)	10373 (50759)	3672 (17612)
Per capita income for the 0-26k income bracket	12061 (1746)	13281 (1205)	12975 (1263)	12217 (1719)
Number of income earners between 26,000 a€nd 55,000 €	631 (1744)	728 (1701)	3163 (19402)	903 (6563)
Per capita income for the 26-55k income bracket	33369 (1807)	33635 (895)	33831 (864)	33431 (1704)
Number of income earners over 55,000 €	112 (388)	134 (503)	754 (6111)	181 (2030)
Per capita income for the 55-120k income bracket	70893 (36658)	78287 (28078)	82231 (21528)	72447 (35181)

Figures

Figure A.1: Density and highway access for LMAs with e-commerce presence

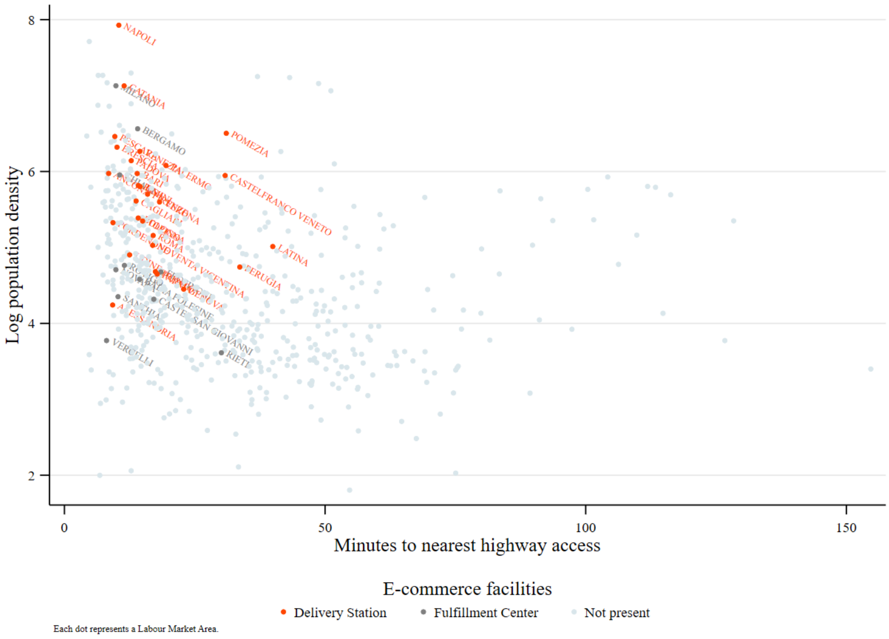


Figure A.2: Share of urban LMAs by e-commerce presence

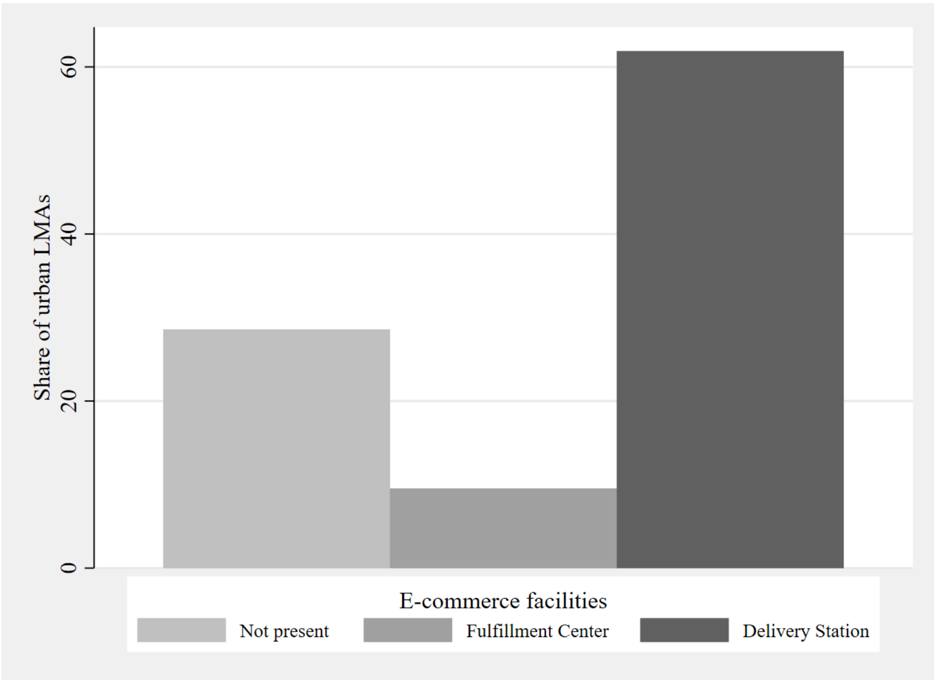


Figure A.3: Analysis of wage impact using a centroid distance measure

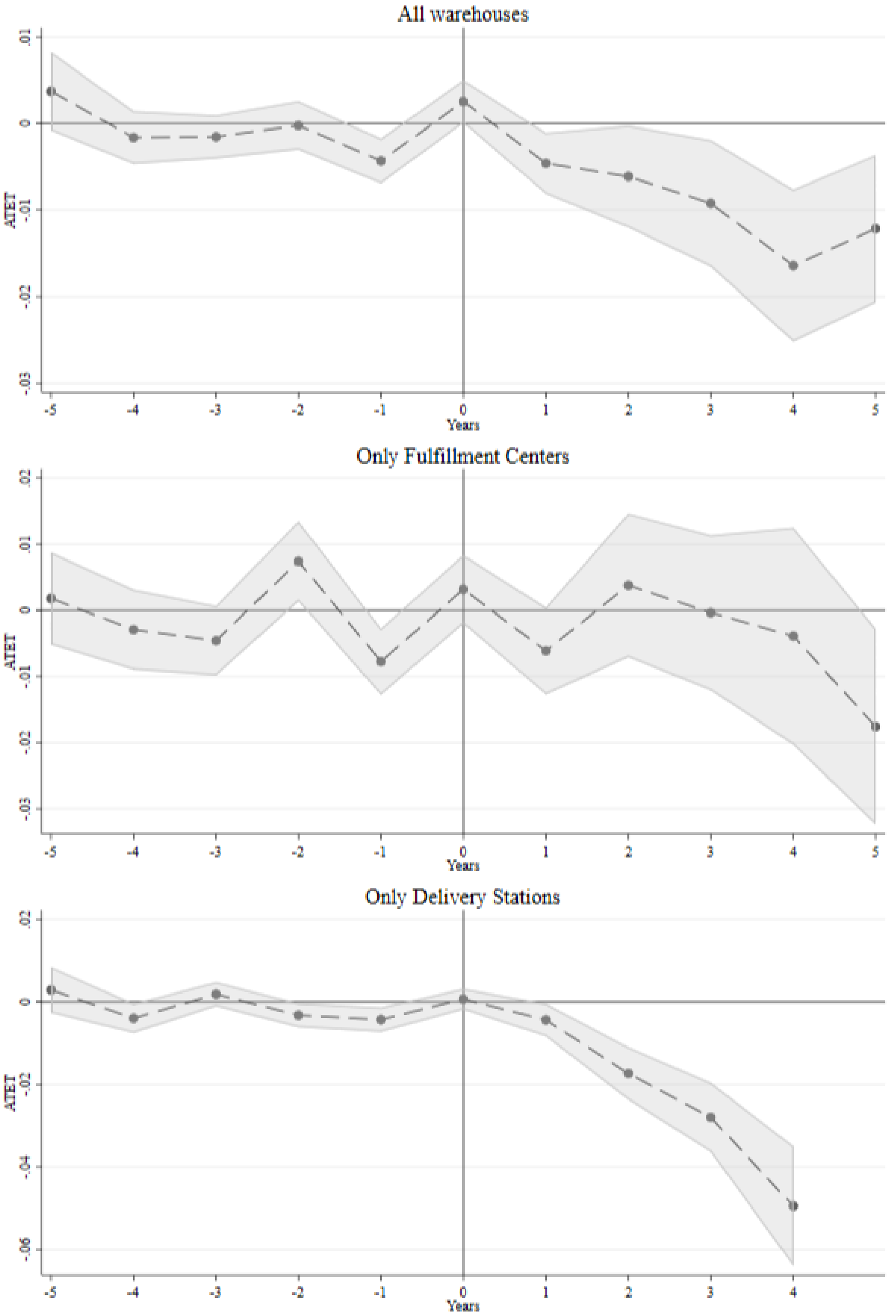


Figure A.4: Analysis of employment impact using a centroid distance measure

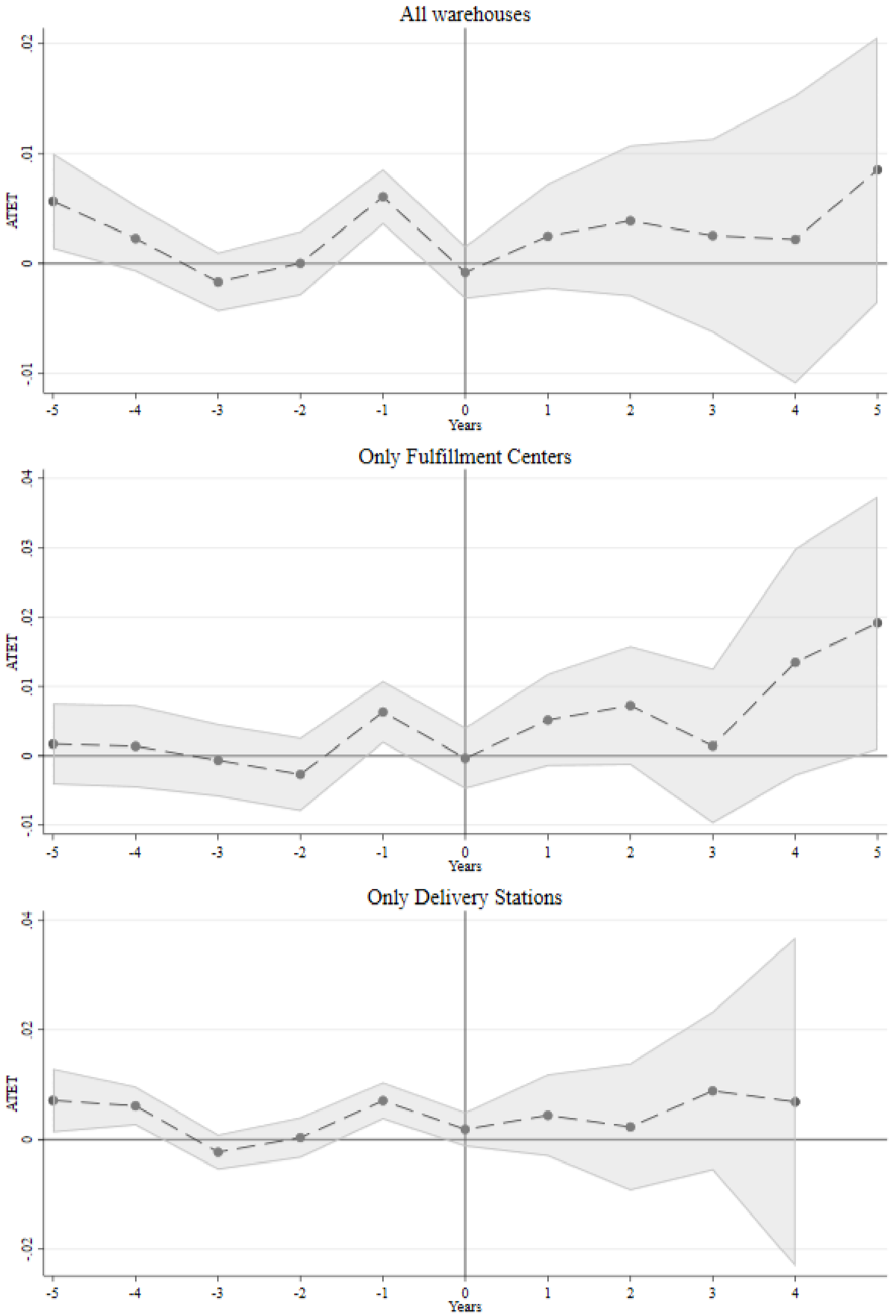


Figure A.5: Analysis of wage impact excluding the Milan Labour Market Area

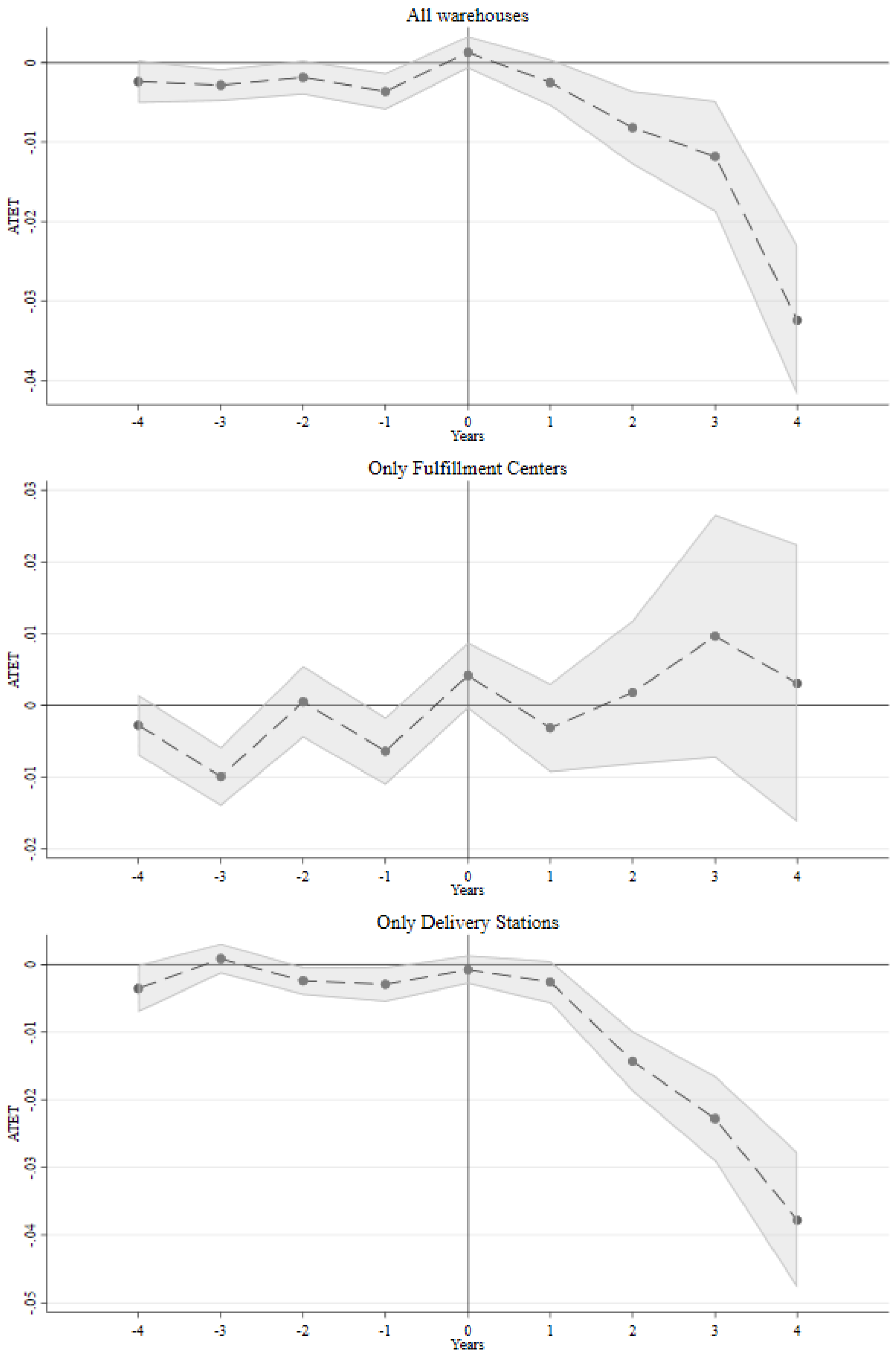
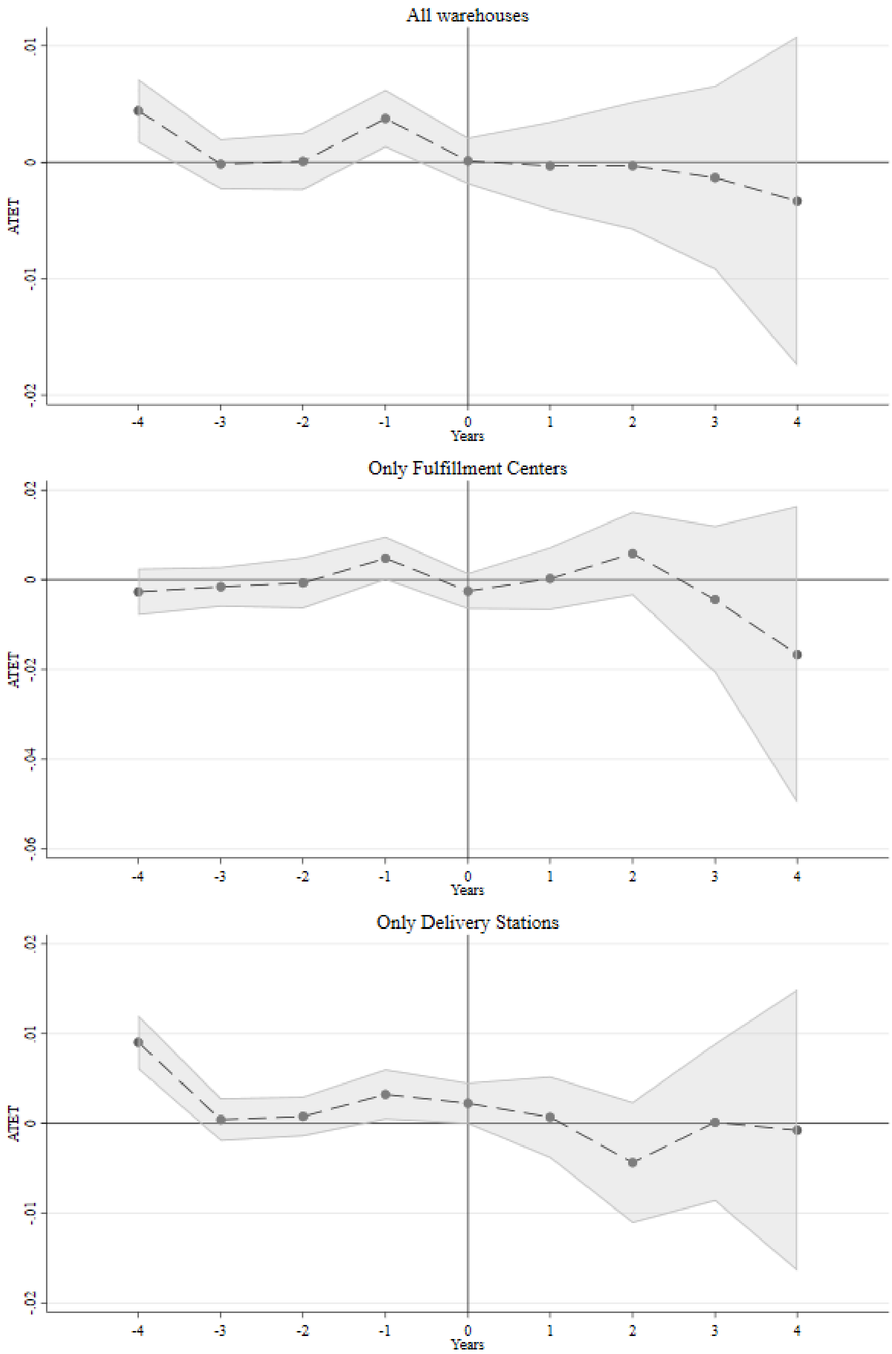


Figure A.6: Analysis of employment impact excluding the Milan Labour Market Area



Chapter 2

The organisational responses of platform-dependent firms

As outlined in the Introduction (Table 1), the advent of online digital platforms presents substantial challenges for internal organisational arrangements, so that the workplace may become fissured, depending on the needs of the platform for firm income and thus for organisational stability. Building on well-established research underscoring the critical role of structural flexibility in enabling firms to thrive under competitive uncertainty (Allaire and Firsirotu, 1989; Ashford et al., 2007; Davis-Blake and Uzzi, 1993), we argue that firms engaging with platforms to reach customers are more likely to adopt short-term contracts, contingent labour, and other non-standard employment relationships (NSERs) as adaptive mechanisms to buffer the risks and vulnerabilities associated with platform participation (Cutolo and Kenney, 2021; Stark and Vanden Broeck, 2024). These adjustments are not a response to market volatility (Davis-Blake and Uzzi, 1993), but serve as safeguards against vulnerabilities inherent in platform participation, including opaque algorithmic control and sudden unilateral policy changes. Accordingly, we propose that the intensity of these effects varies according to firms' structural characteristics and competitive strategies, which condition their degree of platform dependence.

Recent scholarship has increasingly turned its attention to how firms strategise to mitigate the vulnerabilities imposed by platform participation. Much of the extant work has focused on external strategic responses that allow firms to "adapt to the new environment of platforms and undercut their dependence on them" (Balsiger et al., 2023). These tactics include forging alliances with other firms experiencing similar conditions (Kuhn and Galloway, 2015), diversifying across multiple platforms (Cutolo et al., 2021), trying to create alternative income streams (Gastaldi et al., 2024), or even invoking government intervention, as in the recent class-action lawsuit from more than 10,000 hotels against Booking. However, despite the growing interest in the relationship between platforms and labour dynamics (Aloisi and De Stefano, 2022; Kuhn and Maleki, 2017; Vallas and Schor, 2020), virtually no attention has been placed on exploring whether platform participation also influences a firm's internal organisational adjustments, especially those related to the workforce and employment arrangements.

To empirically test these arguments, we utilise a novel dataset from the Digital Platform Survey (DPS), conducted by the National Institute for Public Policy Analysis (INAPP) to monitor Italian companies in the restaurant and hospitality sectors. The present analysis focuses on 20,638 firms

(13,739 observations in the restaurant industry and 6,899 observations in the hospitality sector) with at least one employee, among which 6,920 used digital platforms to reach customers. This analysis indicates that firms adopting platforms to reach customers are approximately 5% more likely than comparable non-platform-based businesses to adopt non-standard employment relationships. Consistent with the theoretical predictions, we show that this effect is more (less) pronounced for platform-dependence-amplifying (reducing) contingencies, such as size, multihoming, engagement with dominant platforms, and platform-specific investments. The positive association between the use of digital platforms and the adoption of non-standard employment relationships is confirmed (although with a smaller magnitude) by a Difference-in-Differences fixed-effects estimation based on a subsample of companies observed in 2020 and 2021. This exercise indicates that companies starting to use platforms in 2020 are more likely to rely on NSERs in 2021 (1.8% increase in non-standard employment relationships).

By systematically investigating firms' internal structural responses to platform participation, the study makes two significant contributions. First, to the best of the author's knowledge, it is the first to illuminate how existing firms configure their internal employment strategies in the face of platform participation, thus enriching the understanding of organisational responses and firms' agency in the platform economy (Cenamor, 2021; Cutolo and Kenney, 2021; Kude and Huber, 2025). Second, the findings extend the discussion on digital platforms and labour (Garcia Calvo et al., 2023; Vallas and Schor, 2020), by demonstrating that their influence penetrates beyond the direct mediation of work practices (e.g., Scott and Orlikowski (2012)), and the introduction of ambiguous and precarious employment statuses (Kuhn and Maleki, 2017; Sundararajan, 2017), to indirectly affect employment relationships via the constellation of firms participating in platform economy. In illuminating these dynamics, the study advances current understanding of how platforms' infrastructural power affects the internal employment relationships, thereby opening new avenues for future scholarship and offering critical insights for policy-makers. The rest of the chapter is structured as follows: Section 2.1 provides a theoretical background reviewing the relevant literature; Section 2.2 outlines the research design and the empirical strategy; Section 2.3 displays results, while Section 2.4 discusses them and concludes.

2.1 Theoretical background

2.1.1 The platform economy

Digital platforms have seamlessly woven themselves into the fabric of modern life, transforming everything from how we shop and stream media to how we book travel and even find romantic partners (Stark and Pais, 2020). For all these needs and more, digital platforms have coalesced into powerful intermediaries that enhance the efficiency of interactions between consumers and producers (Evans and Schmalensee, 2016; Parker et al., 2016). Platforms are reorganising ever more industries (Kenney et al., 2021) and thus forcing traditional companies to enter markets in which platforms intermediate the relationship with customers. The sheer scale and centrality can be seen by the fact that in April 2023, Amazon was the most visited online marketplace in the United States, with about 2.2 billion visits per month (Statista, 2025); in 2024, 43% of travelers used digital platforms for booking hotels, and Uber Eats, one of the most popular food delivery service, is used by more than 88 million users across the globe. As a result, an ever-growing number of businesses across industries find that thriving in today's economy requires active participation in these platform-mediated markets. Given their extensive influence, it is no surprise that digital platforms are under intense scrutiny for the influences they exert over platform-based businesses and society writ-large (Belleflamme and Peitz, 2021; Jacobides et al., 2024; Jacobides and Lianos, 2021).

There has been much research into how platforms facilitate efficient market interactions, emphasizing their capacity to enable new business opportunities. By serving as matchmakers, platforms lower entry barriers, reduce search costs, and enhance transaction efficiency, particularly for new or small-scale enterprises (Nambisan et al., 2018; Von Briel et al., 2018). Despite the fact that these platforms offer tremendous opportunities, their structural realities reveal contradictory effects for the firms using them to reach customers. Platform-organised marketspaces differ markedly from conventional markets, as they are novel institutional arrangements where the platform itself functions as the central hub, leveraging network effects to "tip" or control the market (Gawer, 2022; Jacobides et al., 2018; Parker et al., 2016; Stark and Pais, 2021). Due to the resulting winner-take-all (or most) dynamics, reliance on it is not merely a choice, but it is almost necessary (Jacobides and Lianos, 2021; Khan, 2016). As a consequence, by building their business on top of platforms, firms become directly dependent on them for their performance and, if the market is sufficiently concentrated, survival (Cutolo and Kenney, 2021).

This platform-dependence is further exacerbated by the fact that digital platforms are not merely neutral transactional spaces but highly contested spaces where power asymmetries shape and constrain business practices (Hunt et al., 2025; Hurni et al., 2022). Platform power is ultimately embedded and expressed not only in its technological infrastructure - including application programming interfaces (APIs), software development kits (SDKs), rating systems and recommendation algorithms - but also in the unilateral control over the information and data produced by all participants (Alaimo and Kallinikos, 2024; Gregory et al., 2021). In addition, platforms are effectively private regulators (Boudreau and Hagiu, 2009; Parker and Van Alstyne, 2010), as they set rules and design incentive systems and control mechanisms to orchestrate desired actions by all the participants (Altman et al., 2022; Chen et al., 2022; Scholten and Scholten, 2012; Wareham et al., 2014). For instance, platform owners can promote specific offerings (Rietveld et al., 2021) and directly orient visibility and channel users' behaviors on the platform (Zhou and Zou, 2023). Similarly, platforms not only set but can change at will the fee structure to regulate access (Boudreau, 2010), regulate the division of income between themselves and participants (Chen et al., 2022), and even exclude participants for undesirable behavior (Evans, 2012).

Despite the implicit assumption that it is in a platform owner's best interest to be a trusted party and satisfy all participants (Iansiti and Levien, 2004), concerns have been raised about what many define as the platform using unfair business practices, abusing its power, and exploiting other participants for its own benefit. For instance, platform owners can manipulate search rankings to nudge consumers towards their own offerings or revenue-maximizing choices rather than potential best-value or better options (De los Santos and Koulayev, 2017; Zou and Zhou, 2025). Similarly, by wielding asymmetrical access to data and controlling user traffic, platform owners can leverage privileged information to enter or replicate successful market niches established by firms operating on the platform (Zhu and Liu, 2018). Consequently, firms operating through a platform face a competitive landscape characterised by pervasive uncertainty, vulnerability, and precarity that constrains their strategic agency and impacts overall performance (Aguiar and Waldfogel, 2021;

Curchod et al., 2020; Cutolo et al., 2021; Jacobides and Lianos, 2021; Nambisan and Baron, 2021; Rietveld et al., 2020).

2.1.2 Strategic responses to platform dependence

Despite these challenges, firms do not simply acquiesce and capitulate but, as independent and autonomous actors, they possess agency that they use to develop various coping strategies (Hurni et al., 2022; Kude and Huber, 2025). These responses can be adaptive measures, for instance, investing resources to improve their offering, gaining a more nuanced understanding of the platform environment or its algorithmic systems (Cutolo et al., 2021; Petre et al., 2019), or forging alliances with competitors to exchange best practices and enhance competitive positioning (Chen et al., 2025; Kuhn and Galloway, 2015). In other cases, as firms "constantly work to ameliorate in their favour the balance of bargaining power between them and platform sponsors" (Daymond et al., 2023), businesses may try to reduce their dependence on a single platform by developing multi-homing or multichannel strategies (Chen et al., 2022; Gastaldi et al., 2024; Cennamo and Tavalaei, 2020; Wang and Miller, 2020). In other cases, firms operating on platforms may develop tactics that diverge from the goals and rules laid out by the platform owners. For instance, firms might attempt to evade the affordances and regulations set forth by platform owners through algorithmic manipulation, fake reviews or disintermediation of a platform through establishing a direct connection with customers (Cameron, 2022; Gu, 2024; He et al., 2022; Luca and Zervas, 2016; Wu et al., 2020). As an illustration, hotels often invest resources to try to direct potential customers to their own website (Balsiger et al., 2023).

While it is important to understand the dynamic and sometimes contentious relationship between existing firms and the platform owner, the preponderance of this research is concerned with competitive responses, and far less so with internal structural responses. However, a firm's ability to build and reconfigure internal resources is equally important to respond and adapt to an unpredictable business environment (Eisenhardt and Martin, 2000). Drawing on research on work and organisation studies, we suggest that firms' structural coping mechanisms, particularly those employment decisions, represent an important response that firms adopt to manage the uncertainty stemming from platform dependence.

2.1.3 Leveraging workforce flexibility

organisational scholarship underscores the critical importance of structural mechanisms in enabling firms to effectively buffer uncertainty (Allaire and Firsirotu, 1989; Davis-Blake and Uzzi, 1993). One particularly salient approach concerns the formation of a flexible workforce—often actualised through greater use of non-standard employment relationships (NSERs) (Atkinson, 1984; Martínez-Sánchez et al., 2011). Non-standard work relationships refer to all employment relations other than standard, full-time jobs, and include temporary work, contract labour, independent contractors, and on-call work (Kalleberg, 2000; Pfeffer and Baron, 1988). Substantial research shows that firms turn to NSERs as a way to cope with unstable external conditions, whether driven by cyclical demand, regulatory shifts, or broader market volatility (Davis-Blake and Uzzi, 1993; Pfeffer and Baron, 1988; Uzzi and Barsness, 1998), minimizing long-term commitments and preserving operational agility (Kalleberg, 2000; Mangum et al., 1985). Relatedly, engaging contingent or temporary workers also allows firms to quickly plug specialised skill gaps without incurring the long-term costs associated with hiring and training permanent staff (Abraham and Taylor, 1996; Matusik and Hill, 1998).

Building on these insights, we argue that reliance on NSERs represents an important yet under-recognised consequence of the structural risks stemming from participation in platform-mediated markets. Platform-based businesses must frequently respond to technical and operational transitions imposed by the platform owner. For example, the technical resources, such APIs, and SDKs, provided to enable engagement with the platform change and evolve over time (Eaton et al., 2015). Similarly, platform owners often introduce changes in the fee structures, opaque changes in algorithmic logic, and reconfigurations of the platform policies (such as advertising on the Amazon Marketplace) that alter the condition of participation for platform-based business (e.g., Liu et al. (2022); Wu and Zhu (2022); Zhao et al. (2024). These abrupt and unilateral changes create significant challenges for firms' operational strategies and leave them vulnerable to sudden demand shifts caused by changes in platform visibility (Cutolo et al., 2021). Such vulnerability is engendered by the scarce reliance on countervailing strategies, the general conditions of the sectoral markets where platforms are present, and the weakly regulated institutional contexts in which the platform-firm relationship develops.

By relying on temporary workers, firms can more easily and rapidly adjust to these unpredictable shifts and avoid the rigidity and cost burdens associated with permanent labour. Additionally, such workforce flexibility facilitates the pursuit of cost-reduction strategies that may help firms better hedge against financial vulnerabilities stemming from abrupt changes in commission rates or algorithmic visibility. Beyond managing platform-induced demand fluctuations, leveraging temporary workers with expertise in the emerging technologies or new features, rather than retrain their entire core staff, firms can enhance their agility in navigating steep learning curves, ensuring they can adapt and capitalise on, rather than be disadvantaged by platform changes that negatively impact platform-based businesses (Ozalp et al., 2018).

For this reason, we hypothesise that:

Hp1: *Ceteris paribus, firms operating on platforms are more likely than firms not using platforms to adopt non standard employment relationships*

2.1.4 The moderating role of complementor agency

We have argued that this association reflects a coping response to the uncertainty and vulnerability endemic to the techno-economic structure of digital platforms. To test this, we identify key variables that moderate the power asymmetries experienced by platform-dependent firms, thereby also affecting the direct effect of platform participation on reliance on NSERs. Specifically, we examine firm size, firm multihoming, firm engagement with platform leaders, platform-specific investments as potential moderators. This selection is grounded in the notion that the degree of techno-economic dependence on platforms and the resulting risks vary based on firms' structural, competitive, and contextual characteristics (Cutolo and Kenney, 2021; Hurni et al., 2022; Rietveld et al., 2020; Uzunca et al., 2022). Consequently, if the positive relationship observed in the first step is indeed a function of platform-induced risks, we expect it to be more pronounced under conditions of greater dependence and reduced when firms can more effectively mitigate platform power.

Hp2: *The positive relationship between platform participation and adoption of non-standard em-*

ployment relationships will be stronger under dependence-amplifying contingencies and weaker under dependence-reducing contingencies

Firm size

Firm size is the first variable considered. Smaller firms tend to have lower bargaining power vis-a-vis the platform, which limits their ability to negotiate more favourable commissions with platforms and/or be shielded from exploitative platform behaviors (Balsiger et al., 2023; Uzunca et al., 2022). Their constrained resource availability further diminishes their capacity to maintain strategic autonomy by investing in the promotion of alternative channels. In contrast, larger firms often benefit from stronger brand recognition that reduces reliance on platform intermediation.

Hp2a: *The positive relationship between platform participation and adoption of non-standard employment relationships will be stronger for small firms compared to large firms*

Platform-specific investments

Previous research shows that relationship-specific investment is a central element in the theory of the firm (Hart, 1995). Platform participation often requires specific investments, such as acquiring specialized technological knowledge, certifications, or infrastructure (Engert et al., 2022; Wareham et al., 2014). For instance, in the hospitality sector, hotels often buy new software (e.g., channel managers, CM) with direct interfaces to specific platforms. These investments, while important to support a firm's performance on a specific platform, become obviously significantly less valuable outside it. Consequently, making such investments can likely deepen firms' lock-in and increase their vulnerability (Dyer et al., 2018). Therefore, we expect a stronger correlation between platform use and NSERs reliance in the presence of platform-specific investments.

Hp2b: *The positive relationship between platform participation and adoption of non-standard employment relationships will be stronger for firms with platform-specific investments*

Multihoming

Following the same logic, we also expect this effect to be attenuated when firms are better positioned to manage platform dependence. Among the various strategies firms can deploy to mitigate platform power, platform scholars have emphasized the important role of multihoming—the participation in multiple platforms simultaneously (Gastaldi et al., 2023; Hagiu and Wright, 2021). Multihoming enables firms to diversify risk and broaden their market reach, thereby reducing dependence on any single platform (Cutolo and Kenney, 2021; Nzembayie et al., 2024). Accordingly, we anticipate that firms engaging with multiple platforms will exhibit a weaker relationship between platform participation and NSER reliance.

Hp2c: *The positive relationship between platform participation and adoption of non-standard employment relationships will be weaker for firms operating on multiple platforms compared to those operating on a single platform*

Engagement with the dominant platform

Another key factor influencing firms' experience of platform induced risk is the competitive dynamics of the platform. Prior research suggests that as platforms mature and consolidate their market dominance, they increasingly prioritize profit-maximizing strategies that often come at the expense of firms operating within their ecosystems (Gawer, 2022; Rietveld et al., 2020), of consumers, and ultimately of all external stakeholders, including governments (Doctorow, 2025). This shift in governance practices heightens uncertainty and precariousness for participating businesses. Accordingly, we expect that engagement with platforms holding substantial market shares will be positively associated with NSER reliance.

Hp2d: *The positive relationship between platform participation and adoption of non-standard employment relationships will be stronger for firms operating on dominant platforms compared to those operating on another platform*

To summarise, we hypothesise that firms' engagement with platform market leaders, and platform-specific investments will amplify (i.e., positively moderate) the relationship between platform participation and reliance on NSERs, whereas multihoming and firm size will mitigate (i.e., negatively moderate) this effect. Table 1 summarises the variables we considered to examine the dependence mechanisms underlying the association between platform participation and reliance on NSERs.

Table 2.1: Tests and associated predictions for dependence mechanisms

Variable	Operationalisation	Rationale	Prediction on NSERs
Size	Categorical variable based on the OECD size classes by number of employees. 1= Micro firms (1-9 employees) 2= Small firms (10-49) 3= Medium-sized firms (more than 50).	Smaller firms are more prone to dependence.	Positive relationship between micro firms (compared to small ones) and use of NSERs, and negative for medium-size firms (compared to small ones).
Platform-specific investment	Binary variable: 1 if the company has undertaken specific investments to work with a platform (e.g., equipment, advertising, visibility in online rankings); 0 otherwise. (Based on specific DPS item)	Firms making platform-specific investments are more locked-in, therefore experience higher levels of dependence.	Positive correlation between platform-specific investment and wider use of NSERs.

Multihoming	Binary variable: 1 if a firm undertakes multihoming, i.e., using more than one third-party online platform at the same time; 0 otherwise (Based on Specific DPS information regarding the name of the main platforms companies rely on.)	Firms using multiple platforms to access their customers reduce their overall level of dependence.	Negative correlation between the use of multihoming and NSERs.
Engaging with platform leader	Binary variable: 1 if firm engage with the leading platform (Booking.com in hospitality and Just Eat in restaurants), 0 otherwise. (Market leaders are identified leveraging specific DPS information regarding the name of the main platforms companies rely on.)	Firms operating on dominant platforms experience a higher level of dependence.	Positive correlation between the use of dominant platforms and reliance on NSERs.

2.2 Research design

2.2.1 Setting the scene

To investigate the relationship between digital platforms and firms' structural responses, we focus on the Italian restaurant and hospitality industries.

The Italian setting is particularly suitable for testing the theoretical arguments for at least two reasons. First, Italy has recently experienced a rapid and extensive diffusion of digital platforms, especially within the service sector. In these industries, online platforms provide several essential functions, such as reservation management, reviews, payment services, and last-mile logistics (Balsiger et al., 2023; Fradkin, 2017; Guarascio et al., 2017; Scott and Orlikowski, 2012). As platforms have become increasingly central, firms now face substantial financial and operational dependence on the platforms' decisions. Specifically, they effectively control access to customers— and are able to withhold customer data from the firms—and can even pressure them to modify prices or participate in promotions by rewarding compliance (or punishing defiance) with higher (or lower) online visibility (Stark and Vanden Broeck, 2024; Balsiger et al., 2023; Collison, 2020). Second, over the past two decades, Italy has experienced significant growth NSERs, facilitated by regulatory changes that expanded the types of non-standard contracts and relaxed the restrictions on their use (Barbieri and Scherer, 2009). Both the restaurant and hospitality industries are characterised by a strong reliance on NSERs, partly due to the seasonal variability of demand. These two features—substantial platformisation and the widespread use of NSERs—make the Italian restaurant and hospitality sectors a suitable empirical context for examining how firms adapt their employment strategies in response to platform dependencies.

The two industries (hospitality and restaurants) under analysis share some characteristics. The average firm size is small (between 5 and 6 employees), as family restaurants and small hotels dominate the Italian landscape, and micro-firms such as B&Bs and fast-food takeaways are on the rise. About 2 employees in each enterprise have a non-standard employment relationship, mostly fixed-term, leading to a share of NSERs over total contracts around 28% in the industry (Centra et al., 2024).[1] Restaurants and hospitality firms do however differ in their degree of reliance on platforms: 88% of restaurants did not use them in 2021, while the number is much lower for hotels (23.7%), which platformised much earlier through online travel agencies such as Booking and TriVaGo (Kergroach and Bianchini, 2021; Costa et al., 2021b). The hospitality sector is more vulnerable to platform power in two respects. First, as specified above, platforms are much more widespread, and a single operator, among them, is dominant. Booking.com takes the lion's share as the main point of access to the market for most consumers, and engages in practices that decrease the complementor's cut by forcing rebates, increasing commissions for bookings, advertising and positioning services (Balsiger et al., 2023). Second, hotels face competition from bed & breakfasts: the latter exhibit a leaner labour organisation, in part adapting (and stemming from the availability of) online markets. Larger structures, instead, are more susceptible to demand disruption (Costa et al., 2021a).

2.2.2 Data sources and variables

To gather data on the firms in the restaurant and hospitality sectors, we use a unique data source, the Digital Platform Survey (DPS) conducted in 2022 by the Italian Institute for Public Policy Analysis (INAPP). The DPS provides comprehensive data on the entire population of businesses operating in the restaurant and tourism sectors. Specifically, it collected detailed information on firms' access to digital markets, their relationships with platforms or in-house digital infrastructures, as well as performance indicators, organisational features, and the quantity and quality of employment among surveyed firms. While most data refer to 2021, certain variables—including turnover, employment, and investment figures—also include information from 2020 and 2019. After excluding firms with no employees and firms that have existed for less than one year, the final sample includes 20,638 firms operating as hotels, tourist resorts, guesthouses, and bed-and-breakfasts (B&Bs) in the tourism industry, as well as full-service restaurants and take-away food establishments in the restaurant sector. Of these firms, 6,920 (33.5%) have been using digital platforms to sell goods and services for at least one year [2]. The dataset comprises 13,739 observations in the restaurant industry (1,650

[1] Slightly overrepresented in the unweighed sample.

[2] This selection is motivated by our interest in examining how the use of digital platforms influences the share of NSERs at the company level in 2021. Therefore, we restrict our analysis to companies that have operated on digital platforms for at least one year (i.e., those that began using a platform no later than 2020). For comparison reasons, we also exclude any companies not working with platforms but that have existed for less than one year (i.e., as well as those established before 20209. Additional analyses (available upon request) confirm that our results hold when

of which use platforms, representing 12%) and 6,899 observations in the hospitality sector (5,270 of which use platforms, representing 76.4%). To deepen our analysis, we complement the DPS data with geographic information from the Italian Statistical Atlas of Municipalities (ASC-Istat) and the Italian Ministry of Economics and Finance (MEF) [3].

2.2.3 Empirical strategy

To empirically test these theoretical arguments, we follow a two-step approach. First, we present evidence that firms engaging with platforms employ a higher proportion of NSERs compared to non-platform using firms. Next, we conduct various tests to examine the underlying mechanism driving this effect, specifically the structural responses to uncertainty resulting from platform dependence, focusing exclusively on those companies using platforms to reach customers.

2.2.4 Estimation

As a first step, we estimate the share of NSERs in company i as a function of the extent to which the company operates on digital platforms, a vector X_i of firm level controls, and a vector Γ_m of geographical controls. Given that the dependent variable takes values between 0 and 1, we employed a fractional probit model (Papke and Wooldridge, 1996; Villadsen and Wulff, 2021), according to the following specification:

$$NonStandardEmploymentRelationships_i = \alpha_0 + \beta_1 Plat_i + \beta_2 X_i + \beta_3 \Gamma_m + \theta_r + \delta_s + \varepsilon_{imrs} \quad (2.1)$$

Following prior research (Pfeffer and Baron, 1988), we measure $NonStandardEmploymentRelationships$ in company i as the share of fixed-term, collaboration, and on-call contracts over total employment in 2021. These three are the more common forms of non-standard employment used in Italy and, in particular, in the industries included in the analysis. $Plat_i$ is the main explanatory variable and captures whether or not a firm uses a third-party online platform for sales purposes in 2020. This dummy variable was derived from a specific item in the DPS survey, which asks: "The company sells its products or services through: (a) proprietary digital channels (or those of the group to which the company may belong), such as: website, instant messaging services, WhatsApp, custom mobile app; (b) digital channels owned by other economic operators that facilitate or mediate sales (e.g., Airbnb, Deliveroo, Booking); (c) traditional non-digital channels (store, point of sale, sales agents, or other forms of traditional mediation, including exclusive contracts with a single client, etc.)". If option b) is selected, then another question asks whether the third-party digital channels are digital platforms. Therefore, $Plat_i$ takes a value of 1 if companies selected option b) in response to the question, and then subsequently answered affirmatively to the follow-up question.

At the firm level, we controlled for several characteristics that may affect a firm's employment relationship, such as its size (number of employees in logarithmic form), age, investment amount,

also considering companies initially excluded—namely, those that started using platforms in 2021 or 2022, as well as those established after 2020.

[3] While ASC-Istat includes information on population density and other physical characteristics of municipalities, the MEF provides details on average incomes in each area.

and turnover per worker expressed in logarithmic form. We also included controls for the use of proprietary online channels and legal incorporation. To account for demand volatility, we created two specific measures: (i) turnover variation over the two years preceding the survey, and (ii) employment change over the two years preceding the survey, both in in logarithmic form. All variables are lagged to mitigate potential simultaneity issues. All firm-level controls are included in X_i of equation [1], with β_2 representing the respective coefficients. we also control for sub-sectors - δ_s - (hotel, resort, BB, full-service restaurant, and takeaway-only).

Moreover, at the geographical level, we control for elements associated with demand volatility and market uncertainty, for instance whether the company is located in a municipality in a mountain area (above 600 meters in elevation), a beach destination or coastal area, or on an island. Additionally, we account for other contextual factors that may affect firms' access to workers, for instance the population density of the municipality, the average income of the municipality in logarithmic form, and the average rent in the municipality. Given the significant geographical heterogeneity across Italian municipalities in terms of structural and productive characteristics, we also include macro-regional dummies (θ_r). Standard errors have been clustered at the sectoral (s), regional (r), and municipal (m) levels. The term ε_{imrs} represents the error term, capturing residual variables not accounted for in the model.

An important concern is that, ideally, we would need to compare the employment decisions of highly similar companies both on and off digital platforms. However, companies do not join platforms randomly and consequently there are likely significant differences between firms operating on platforms and those that do no. Therefore, to increase the confidence in these results, we restrict the analysis on firms having a common support after implementing Coarsened Exact Matching (CEM) (Iacus et al., 2012), which allows for the comparison of firms adopting digital platforms with otherwise similar firms that do not rely on them. Firms were matched based on the following characteristics: size class (0-5, 6-15, 16-50, 51+), geographical area (North-West, North-East, Center, South and Islands), population density, per capita income in the municipality in 2021 (logarithmic form), per capita rent in the municipality in 2021 (logarithmic form), urban area, rural area, mountain area, coastal and beach area, subsectors (hotels, bbs, restaurants, takeaways).

Finally, to rule the possibility that our results are distorted by the Covid-19 pandemic, we used the share of non-standard employment in 2019 as dependent variable and a subset of controls referring to 2019 and previous years.

To test the effect of the moderators that can increase or reduce companies' reliance on non standard work arrangements, we estimate equation 2.2, focusing exclusively on companies using digital platforms and concentrating our attention on four key mediating factors that we expect to either mitigate or reinforce firms' dependency on platforms.

$$\begin{aligned} NonStandardEmploymentRelationships = \alpha_0 + \beta_1 MediatingFactor_i + \beta_2 X_i + \beta_3 \Gamma_m + \\ + \theta_r + \delta_s + \varepsilon_{imrs} \end{aligned} \tag{2.2}$$

where
$i \in \{Plat = Yes\}$.

The variable $MediatingFactor$ alternately takes the value of 1 in the following cases: if the platform-dependent company is a micro-firm (0 otherwise); if the firm adopts a multihoming strategy (0 otherwise); if the firm operates on a dominant platform (0 otherwise); and if the firm has made platform-specific investments (0 otherwise). Firm level – X_i – and geographical controls – Γ_m – are the same as those included in equation 2.1, as well as sub-sectors δ_s and macro-regional θ_r dummies.

Descriptive statistics for the main variables used in the analysis are presented in Table B.1 in Appendix B. As Table B.1 shows, companies using digital platforms have a slightly higher percentage of NSERs (34%) compared to those not using digital platforms (30%). However, it is interesting to note that among precarious forms of employment, companies relying on platforms have nearly double the number of employees on fixed-term and collaboration contracts, and more than four times the number of on-call contracts, which are the most precarious forms of work arrangements.

Lastly, to address potential endogeneity concerns, we perform a difference-in-differences (DiD) regression analysis (Donald and Lang, 2007) focusing on firms that adopted a platform in 2020—a year uniquely shaped by the outbreak of the COVID-19 pandemic, which compelled many businesses to rely on digital platforms to market their products and sustain revenues during lockdowns (Ravenelle et al., 2021; Pirone et al., 2020). We exploit a peculiar characteristic of the DPS: information on turnover, personnel, and contractual relationships was collected for three years: 2019, 2020, and 2021. Therefore, we obtain a panel-like structure of the data including only these variables (see also Table A.4 in the Appendix). As the other variables are time-invariant, they are used in the matching process, but they are otherwise cancelled out by the difference-in-differences structure. The pandemic can be regarded as an exogenous shock that accelerated firms' entry into the digital economy, thereby providing a natural setting for a counterfactual analysis. In this framework, treated firms are those adopting platforms in 2020, while the control group comprises otherwise similar firms that did not. More specifically, we employ the CEM technique to pair treated firms with suitable controls, matching on subsector (hotels, B&Bs, restaurants, and takeaways), geographical characteristics, and the share of NSERs in 2019 and 2020. Such approach ensures that the matched firms exhibited similar pre-treatment trends prior to platform adoption (Figure A.1 in the Appendix). This procedure assigns weights to control observations and excludes those lying outside the common support – i.e., firms too dissimilar from adopters to serve as valid controls. We include a firm identifier and a year identifier (firm- and year-fixed effects) to account for potential unobserved heterogeneities. Therefore, the following equation is estimated:

$$NonStandardEmploymentRelationships_{i,t} = \beta_1 Plat_i + \beta_2 (Plat_i * 2021) + \beta_3 (Plat_i * 2019) + \psi_i + \lambda_t + \varepsilon_{i,t} \tag{2.3}$$

where $NonStandardEmploymentRelationships_{i,t}$ captures the share of NSER for each firm i in year $t = 2019, 2020, 2021$. Our key explanatory variables, $Plat_i$ is a dummy taking value of 1 whether the firm has adopted a digital platform in 2020, and 0 otherwise (control group). The year 2021 is a time indicator for the post-treatment period and the year 2019 is the pre-treatment one; then the interaction term $Plat_i * 2021$ identifies the DiD effect of digital platform, while the $Plat_i * 2019$ allows us to test the common trends assumption (CTA) (Donald and Lang, 2007; Card and Krueger, 1993) with respect to 2020 – reassuring us that we are comparing firms with similar patterns of NSER use prior to adoption. ψ_i and λ_t are panel and time fixed effects, respectively. Lastly, $\varepsilon_{i,t}$ is an error term clustered at the panel-time level.

2.3 Results

Tables 2.2 and 2.3 presents the results of the analysis. we find that, on average, β_1 —the coefficient associated with the use of digital platforms—is positive and significant across all specifications (Model 1-4) indicating that, ceteris paribus, firms using digital platforms are more likely to rely on NSERs compared to non-platform using firms. More specifically, holding other control variables constant (Model 2) the use of platforms to reach customers is associated with a 5% higher share of NSERs. Importantly, it is worth noting that we include the log change in turnover and employees over the 2019-2021 period as a control variable. Both coefficients are positive and significant, implying that, as expected, demand dynamics do affect companies' decisions concerning NSERs. Nonetheless, this does not eliminate the significance of platform participation as an additional driver.

Table 2.2: Effect of platform adoption on the firm-level share of non-standard employment relationships

% of NSERs	(1)	(2)	(3)	(4)*
Use of platforms	0.0891***	0.0509*	0.0574*	0.0659*
	(0.0152)	(0.0216)	(0.0227)	(0.0275)
Firm-level controls	NO	YES	YES	YES
Geographic controls	NO	YES	YES	YES
Constant	-0.513***	3.305***	3.632***	4.043***
	(0.00871)	(0.870)	(0.997)	(0.934)
Observations	20,472	20,331	20,325	16,715
χ^2	34.56	1576	1343.47	1164
R^2	0.000837	0.0468	0.0542	0.0542
Base log-pseudolikelihood	-12749	-12663	-10906	-10448
Log-pseudolikelihood	-12738	-12070	-10906	-9882
clusters		5,549	5,547	5,142

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are clustered at the municipality, region, area, industry level.

*The population for 2019 excludes those firms that are born after 2018. All firms which joined platforms after 2018 are likewise excluded. Controls for 2019 are either time-invariant or simultaneous due to data availability. Firm-level controls are: sub-sectors, log of number of employees 2019, firm age, legal incorporation, use of website, log of turnover per capita 2019. Geographic controls do not change.

As the CEM model reports (Model 3), β_1 is still positive and significant, suggesting that the differences between firms using or not using platforms is not driving the results. Model 4 replicates our results focusing on the pre-Covid period: albeit only with simultaneous and time-invariant controls, estimates appear consistent, confirming Hypothesis 1.

Table 2.3: Effect of platform adoption on the firm-level share of non-standard employment relationships – Moderating factors

	(5)	(6)	(7a) Restaurants	(7b) Hospitality	(8)
Firm-size: Micro-firms	0.229***				
	(0.0476)				
Firm-size: Medium-large firms	-0.502***				
	(0.0813)				
Multihoming		-0.0677***			
		(0.0262)			
Using platform market leader			-0.00934	0.156***	
			(0.0502)	(0.0519)	
Investments on the platform					0.0744***
					(0.0274)
Firm-level controls	YES	YES	YES	YES	YES
Geographic controls	YES	YES	YES	YES	YES
Constant	3.697***	4.136***	1.953	4.812***	4.253***
	(1.332)	(1.334)	(2.122)	(1.610)	(1.338)
Observations	6,830	6,830	1,622	5,208	6,830
χ^2	801.4	790.7	123.5	763.1	795
R^2	0.0676	0.0653	0.0238	0.0863	0.0653
Base log-pseudolikelihood	-4358	-4358	-1037	-3321	-4358
Log-pseudolikelihood	-4064	-4074	-1013	-3035	-4074
clusters	2184	2184	697	1487	2184

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are clustered at the municipality, region, area, industry level. Base category for firm size is Small firms.

Model 5 examines the relationship between company size and the share of NSERs among platform dependent firms. As predicted, we find that micro-firms (fewer than nine employees) are more likely than small firms (10–50 employees) to rely on NSERs (β = .229, p < .001).

Specifically, micro-firms have, on average and ceteris paribus, a 22% higher share of NSERs. By contrast, the coefficient for medium firms (more than 50 employees) is negative and significant, supporting the hypothesis that the size of a company operating on platforms affects the degree experiencing greater dependence on platforms.

Model 6 examines the impact of multihoming. As hypothesised, when companies use more than one digital platform, their reliance on NSERs is reduced: on average and ceteris paribus, multihoming firms have 6% fewer NSERs compared to those using a single platform. Notably, multihoming appears to weaken the relationship between platformisation and the use of NSERs, suggesting that this strategy may reduce their dependency on any single platform, and consequently the need to rely on NSERs.

we also find that companies relying on dominant platforms (i.e JustEat in the restaurant sector, Model 7a, and Booking in the hospitality industry, Model 7b) exhibit a relatively higher share of NSERs. However, the coefficient is positive and statistically significant only for the hospitality sector, where companies engaging with the market-leading platform are associated with a 15% higher share of NSERs compared to those working with other platforms. This finding supports the idea that dependence tends to be stronger when platform services are concentrated in the hands of one or a few dominant platforms. Another explanation for the significance in the hospitality sector is that while platforms in the restaurant industry tend to specialise in specific functions (e.g., Yelp for reviews, The Fork for reservations, and Takeaway for delivery), in hospitality, functional integration prevails (e.g., Booking.com integrating marketplace, reviews, and reservations), thereby increasing the power asymmetries.

Lastly, Model 8 presents the results for firms that have made platform-specific investments. On average and ceteris paribus, these firms exhibit a 7% higher share of NSERs compared to other companies also engaging with platforms but without undertaking such investments. Therefore, we can assess that platform-specific investments may create a lock-in effect, leading to an even stronger reliance on NSERs as an adaptive response to platform dependency.

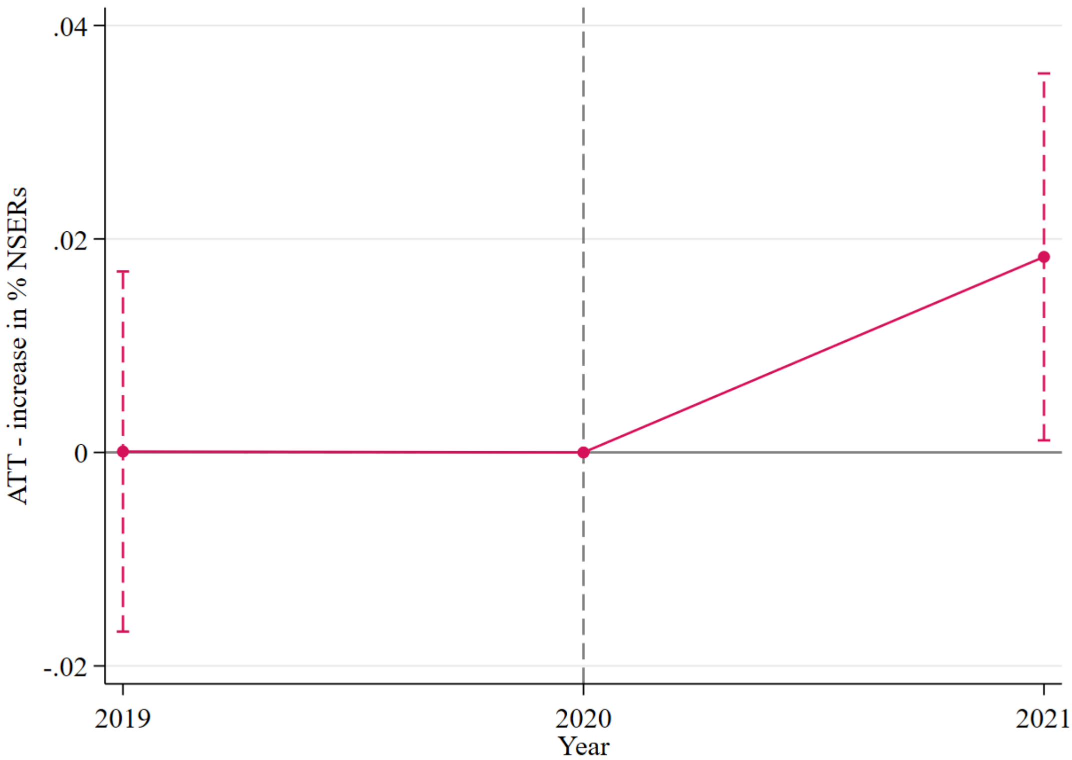
As a robustness check of the main relationship, Table 2.4 shows that, after one year, platform adoption is associated with a 1.8% increase in the share of non-standard employment. This suggests that platform adoption led these firms to rely relatively more on flexible organisational resources compared with their counterparts (Figure 2.1). These findings lend further support to the hypothesis that platform adoption is strongly associated with an increased use of flexible work arrangements (Hypothesis 1).

Table 2.4: Impact of platform adoption in 2020 on firms in the Restaurant and Hospitality sector - Difference-in-Differences with Coarsened Exact Matching

[1em] Use of platforms × 2019	8.34^{-5}
	(0.00861)
Use of platforms × 2021	0.0183*
	(0.00877)
2019	0.0291***
	(0.00540)
2021	0.0122*
	(0.00474)
Constant	0.273***
	(0.00260)
Observations	18,783
Adjusted R^2	0.892
Within adjusted R^2	0.0164
Log-likelihood	17967.1
F-statistic	14.35

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.1: Impact of 2020 platform adoption on non-standard work - Difference-in-Differences with Coarsened Exact Matching



2.4 Discussion and conclusion

Over the past three decades, digital platforms have become significant forces in an increasing number of industries and economic sectors, developing into the “dominant institutional form of the digital age” (Gawer, 2022; Kenney et al., 2021). As a result, for many firms, engaging with digital platforms is no longer a matter of choice but rather a competitive necessity. Existing research has already shown the transformative impact of platforms’ infrastructural power on firms’ competitive strategies (Cutolo et al., 2021; Hagiu and Wright, 2021), highlighting the importance of both harnessing a platform’s resources and mitigating its power (Kude and Huber, 2025). This study provides the first evidence that the dynamics of “platformisation” also affect firms’ structural organisation—specifically, their employment relationships. The analysis indicates that firms using platforms are approximately 5% more likely than comparable businesses not using platforms to adopt NSERs, such as the use of temporary workers, collaboration, and on-call workers. we further demonstrate that this shift can be interpreted as a response to the vulnerabilities and risks engendered by platforms’ power asymmetries. Indeed, factors that heighten a firm’s dependence on a given platform (e.g., platform-specific investments or engagement with dominant platform) amplify the relationship between platform participation and the use of NSERs, while strategies that reduce platform dependence (e.g., multihoming or the size of a firm) attenuate the effect.

The present work makes several important contributions. First, we advance growing management and organisational literature exploring the challenges faced by existing firms as they interact with and through platforms to deliver their offerings to users (Cenamor, 2021; Cutolo and Kenney, 2021; Kude and Huber, 2025; Nambisan and Baron, 2019; Zhu and Liu, 2018). This growing body of work highlights that platform-organised markets are precarious for participants due intense competitive dynamics (Boudreau and Hagiu, 2009), fast-evolving users’ preferences (Panico and Cennamo, 2022; Rietveld and Eggers, 2018), and, perhaps most importantly, the contradictory logics and power asymmetries that characterise their relationship with the platform owner (Curchod et al., 2020; Hurni et al., 2022; Jacobides et al., 2024). In this regard, prior work explicitly recognises the increasing need for firms to develop strategic responses that mitigate the vulnerabilities and the risks endemic to platform participation (Gastaldi et al., 2023; Nzembayie et al., 2024; Wang and Miller, 2020; Wen and Zhu, 2019). Yet, this growing stream of research has largely concentrated on competitive responses and how they affect firms’ financial or innovative performance, overlooking the internal mechanisms a firm may deploy to mitigate these uncertainties.

The present work directly contributes to a better understanding of “the digital platform battlefield and the power dynamics that will continue to shape their societal impacts” (Hunt et al., 2025), by showing that traditional workforce strategies play a critical role in responses to the uncertainties created in platform-mediated markets. Platform dependent firms in fact repurpose established employment strategies to address new forms of instability and precarity stemming from that dependence. our findings thus point to the incompleteness of extant focus on strategic positioning and competitive decisions to understand the consequences of platform power and the responses of platform participants (Hurni et al., 2022; Kude and Huber, 2025), underscoring the need for a more integrated perspective that also take into account the internal adaptations that firms undertake to operate in platform-organised markets.

Moreover, while the findings support the notion that platform participation constitutes an existential experience of uncertainty for firms (Curchod et al., 2020; Cutolo et al., 2021), the empirical evidence indicates that the precarious conditions associated with platform dependence do not manifest uniformly. The differential effects observed in the analysis of the mechanisms suggest that, although all firms relying on platforms are, to some extent, exposed to the threat of platform dependence, the risks and challenges they face vary significantly due to firm-level characteristics, strategic choices, and contextual conditions. This insight adds to recent research aimed at refining the understanding of the features and circumstances that render firms more or less dependent on platforms (Gastaldi et al., 2023; Nzembayie et al., 2024; Rietveld et al., 2020), by suggesting that this dependence is best conceptualised as a multidimensional continuum—or "grayscale"—rather than a singular, monolithic state of precariousness.

This chapter also offers important insight for studies centred on the impact of platforms on labour (Aloisi and De Stefano, 2022; Cirillo et al., 2023a; Garcia Calvo et al., 2023; Kuhn and Maleki, 2017; Vallas and Schor, 2020). While much has been written about the contingent and precarious nature of platform-mediated labour (Schor and Attwood-Charles, 2017), and how platforms' infrastructural characteristics steer and constrain the agency of platform workers (Cameron, 2022; Curchod et al., 2020), there has been far less study of whether the instability brought by platform environments has consequences in terms of employment relationships for the constellation of firms engaging with digital platforms. This indirect effect becomes particularly significant as a growing number of traditional industries are intermediated by platforms (Kenney et al., 2021): our findings suggest that this continued expansion is likely to further increase the number of workers integrated into NSERs—and, consequently, intensify precarity.

Of course, while such strategies can bolster adaptability and mitigate some of the risks inherent in platform participation, they also prompt concerns about broader labour market implications (Kalleberg, 2000). Historically, these types of NSERs were largely concentrated in industries already marked by high volatility; yet the indirect effects of platformisation now appear to be increasing the amount temporary, contingent, and otherwise precarious work across an expanding array of sectors. This trend suggests that, as platforms continue to mature and become ever more constitutive of the modern economy (Kenney and Zysman, 2016; Parker et al., 2016), the relationships between platforms and their broader socio-economic environment will likewise evolve. Although platforms are often viewed as private, closed, managed economic spaces (Altman et al., 2022; Boudreau and Hagiu, 2009), the effects of platformisation reverberate well beyond their immediate boundaries, affecting industries, labour markets, and society at large (Srnicek, 2017). Understanding this is essential to developing strategies and tools to properly address the distribution of risk and benefit between the platform owners and the rest of participants (Jacobides and Lianos, 2021).

This directly brings us to the policy implications of this study. The findings echoes previous works emphasizing the need for well-designed competition policies to limit the power of platforms without compromising the positive effects they have on existing businesses (Cusumano et al., 2021; Jacobides and Lianos, 2021). To address techno-economic dependence and its unintended organisational and structural consequences to materialise, various policy instruments can be considered. Cross-platform competition could be favoured by limiting the share of services (e.g., reservations, marketplace) managed by a single platform in the industry. This would make easier to multihome which, as results have shown, could reduce the uncertainty that platform-dependent firms face. Likewise, measures directed at ensuring algorithmic transparency are crucial to prevent platforms from abusing the power stemming from their control of digital infrastructures and information. In this regard, the EU Digital Markets Act may serve as an effective regulatory anchor, requiring platforms to: provide transparency on the criteria used to manage and adjust rankings and ratings; ensure that companies have access to the input data used to determine these rankings; and refrain from penalizing firms that operate on other platforms or their own proprietary websites. To make sure that such policies are implemented in a timely and effective manner, sector-specific regulatory bodies, including members of employer association and trade unions, could prove very helpful as the nature of firm-platform relationships (and related policy problems) tend to vary significantly across industries.

Moreover, as one of the consequences of platform dependence could be an excessive diffusion of NSERs which, in turn, may lead to a generalised worsening of the quality of employment with potentially negative social and macroeconomic implications, labour policy can also play an important role. Specifically, measures that limit companies' reliance on NSERs can help prevent excessive workforce precarity, especially in industries characterised by high uncertainty. A similar objective might be achieved by restricting the number of times a temporary contract can be renewed for the same worker.

So far, companies have taken relatively little legal action against digital platforms, as they voluntarily accept their terms and conditions and, in theory, always have the option to leave. On the other hand, a number of policy initiatives aimed at countering the power of platforms have been put forth, particularly in Europe (e.g., the Digital Market Act, the Digital Service Act). Yet, to what extent such measures will be actually able to avoid situations of techno-economic dependence remains open question. As discussed, governments should actively safeguard the independence of small-scale producers and, relatedly, counteract the potential indirect effects of platform power on their workforce. This is a crucial point, as the pervasive growth of NSERs can have negative implications from a micro (i.e., non-standard workers tend to face greater uncertainty and this may negatively affect their propensity to consume or to invest in training), macro (i.e., a high incidence of non-standard work can have a negative impact on aggregate demand and, hence, on growth) and social (i.e., non-standard work is not rarely associated with situation of social hardship, including difficulties to meet essential needs at the individual as well as at the household-level) point of view.

Naturally, this study has some limitations that offer opportunities for future research. First, one potential limitation arises from the specific setting in which it was conducted. While we believe these findings generalise to other contexts, cross-country as well as sectoral heterogeneities need to be systematically investigated. Platforms tend to operate differently according to the peculiar structural/institutional context they are dealing with (i.e., relevance of digital vs non-digital channels, country and industry-specific norms protecting non-platform incumbents, data-related regulations imposing algorithmic transparency). As a result, it would be important to empirically assess how companies' adaptive strategies in platform-organised sectors vary depending on country- and industry-specific characteristics, as well as factors such as the level of unionisation, workers' bargaining power, and government interventions. For instance, Spain recently introduced a reform aiming at curbing the use of temporary contracts for workers. Does the presence of different regulations affect firms' internal adjustment to platform uncertainty? Such comparative evidence could be very useful in providing policy advice. Beyond sector-specificities, we can expect that the theoretical mechanisms outlined in this analysis may be generalised to other sectors that have recently experienced similar dynamics, such as, firms selling through a platform, though in each sector there should be specific peculiarities.

Second, while the analysis provides robust evidence accounting for various confounding factors and self-selection, a key improvement would be to strengthen the causal plausibility of the findings. This could be achieved by explicitly addressing unobserved heterogeneity through the inclusion of firm-level fixed effects. In this regard, the availability of longitudinal data can give a substantial help. For instance, this may allow using the Covid-19 pandemic as an exogenous shock to test whether companies facing a different degree of dependency vis-à-vis platforms tend to adopt heterogeneous adaptive strategies, that include managing internal employment relationships. No less important, longitudinal data would enable exploration of the dynamic nature of the firm-platform relationship, in line with one of the key hypotheses put forth by Cutolo and Kenney (2021), which suggests that as time progresses, the uncertainty firms face when interacting with platforms increases.

Lastly, it would be crucial to complement quantitative evidence—possibly based on high-quality administrative data on hiring and labour contract separations—with qualitative studies involving in-depth sectoral and firm-level analyses. This would help further validate the predictions and identify underlying dynamics that quantitative survey data may not be able to adequately capture.

Platforms increasingly consolidate their power as critical intermediaries—both by creating new markets and by restructuring an ever-growing array of traditional industries. The reorganisation of markets by platforms may result in greater precariousness not only by transforming work into gigs, but also in existing firms in traditional industries by increasing the use of “gig-like” employment. The consequences of this kind of labour organisation, characterised by a strong flexibilisation of employment relationships coupled with a systematic recourse to digital monitoring and algorithmic management, are outlined in Chapter III, and coincide with heightened levels of economic insecurity.

Appendix for Chapter II

Tables

Table B.1: Descriptive statistics

	No platform use	Use of platforms	Total
Observations	13,718 (66.5%)	6,920 (33.5%)	20,638 (100.0%)
Dependent variable			
Fixed-term contract employees, 2021	2.364 (8.913)	4.066 (14.470)	2.935 (11.119)
Collaboration contract employees, 2021	0.119 (0.886)	0.248 (2.094)	0.162 (1.413)
On-call contract employees, 2021	0.043 (0.385)	0.182 (3.155)	0.090 (1.855)
Number of employees, 2021	6.647 (18.762)	10.790 (37.139)	8.036 (26.462)
% of non-standard contracts, 2021	0.304 (0.355)	0.336 (0.375)	0.315 (0.362)
Fixed-term contract employees, 2019	2.587 (10.363)	4.338 (14.776)	3.174 (12.053)
Collaboration contract employees, 2019	0.122 (0.958)	0.249 (1.954)	0.165 (1.376)
On-call contract employees, 2019	0.048 (0.528)	0.167 (2.705)	0.088 (1.625)
Number of employees, 2019	7.123 (22.058)	11.123 (33.909)	8.464 (26.692)
% of non-standard contracts, 2019	0.315 (0.360)	0.347 (0.379)	0.326 (0.367)
Firm-level controls			
Firm size (Log number of employees, 2020)	1.631 (0.704)	1.703 (0.912)	1.655 (0.781)
Firm age	16.140 (12.697)	17.282 (14.116)	16.523 (13.201)
Subsectors			
Hotels	(6.3%)	(42.1%)	(18.3%)
Resorts	(0.5%)	(1.1%)	(0.7%)
B&Bs	(5.1%)	(33.0%)	(14.5%)
Restaurants	(73.6%)	(19.8%)	(55.5%)
Take-aways	(14.5%)	(4.1%)	(11.0%)
Legal incorporation of the firm			
Individual enterprise	(42.0%)	(29.6%)	(37.8%)
LLCs, LLPs	(56.9%)	(68.6%)	(60.8%)
PLCs, Inc.s	(0.2%)	(1.0%)	(0.5%)
Cooperatives	(0.9%)	(0.8%)	(0.9%)
Consortia and others	(0.0%)	(0.0%)	(0.0%)
Use of own website	(22.1%)	(74.3%)	(39.6%)
Log of investment per capita 2020 with depreciation	1.820 (3.157)	2.749 (3.884)	2.132 (3.446)
Log of R&D and marketing investment per capita 2020	0.109 (0.794)	0.240 (1.213)	0.153 (0.957)
Log of trademark investment per capita 2020	0.023 (0.373)	0.054 (0.551)	0.034 (0.441)
Log of IT investment per capita 2020	0.379 (1.371)	0.636 (1.773)	0.465 (1.523)
Log of software investment per capita 2020	0.072 (0.604)	0.255 (1.180)	0.133 (0.847)
Log turnover per capita, 2019	9.909 (1.864)	10.119 (1.920)	9.979 (1.886)
Log turnover per capita, 2020	9.574 (1.962)	9.676 (2.055)	9.608 (1.994)
Log rate of turnover change, 2019-2021	-0.310 (1.957)	-0.310 (2.028)	-0.310 (1.981)

Log employees change, 2019-2021	-0.040 (0.346)	-0.043 (0.340)	-0.041 (0.344)
Geographical controls			
Log income per capita in municipality, 2021	9.933 (0.191)	9.963 (0.191)	9.943 (0.192)
Log rent per capita in municipality, 2021	7.161 (0.461)	7.368 (0.475)	7.230 (0.476)
Population density	829 (1,394)	1,045 (1,673)	902 (1,497)
Degree of urbanisation			
Urban	(24.3%)	(32.4%)	(27.0%)
Semi-peripheral	(46.6%)	(38.4%)	(43.8%)
Rural	(29.1%)	(29.2%)	(29.2%)
Mountain	(12.6%)	(16.7%)	(14.0%)
Beach	(34.2%)	(43.6%)	(37.4%)
Island	(0.9%)	(1.5%)	(1.1%)
Coastal	(38.7%)	(46.2%)	(41.3%)
Geographical area of Italy			
North-West	(20.9%)	(18.5%)	(20.1%)
North-East	(25.2%)	(28.4%)	(26.3%)
Centre	(22.1%)	(22.5%)	(22.2%)
South and Islands	(31.8%)	(30.6%)	(31.4%)
Platform-only variables			
Years on the platform		7.640 (5.016)	
Multihoming		(42.5%)	
Platform used in Restaurants			
Just Eat		(24.8%)	
Deliveroo		(18.8%)	
Glovo		(6.6%)	
The Fork		(6.7%)	
Others		(43.0%)	
Platform used in Hospitality			
Booking		(89.0%)	
Airbnb		(4.1%)	
Expedia		(0.8%)	
Others		(6.1%)	
Platform-related investments		(30.1%)	

Standard deviation is reported for continuous variables, while percentages are reported for factor variables. For platform-specific and platform-industry-specific variables, percentages are calculated over the relevant set of observations.

Table B.2: Effect of platform adoption on the firm-level share of non-standard employment relationships - Full table

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS-CEM	OLS 2019
Use of platforms	0.0891***	0.0509*	0.0830**	0.0659*
	(0.0152)	(0.0216)	(0.0318)	(0.0275)
Resorts		-0.151	-0.424	-0.127
		(0.0939)	(0.227)	(0.0977)
B&Bs		-0.322***	-0.379***	-0.176***
		(0.0365)	(0.0699)	(0.0389)
Restaurants		-0.0151	-0.0909	-0.000894
		(0.0331)	(0.0594)	(0.0350)
Take-aways		-0.154***	-0.109	-0.0954*
		(0.0397)	(0.0765)	(0.0433)
Log rate of turnover change		0.0245***	0.00513	
		(0.00468)	(0.0117)	
Log change in personnel		0.245***	0.161*	
		(0.0263)	(0.0786)	
Log number of employees, 2020		0.232***	0.271***	
		(0.0128)	(0.0381)	
Log employees, 2019				0.335***
				(0.0144)
Log turnover, 2019				-0.0165***
				(0.00451)
Firm age		-0.00548***	-0.00469**	-0.00603***
		(0.000608)	(0.00145)	(0.000671)
SRL, SAS, SNC		0.0746***	0.145**	-0.0146
		(0.0191)	(0.0506)	(0.0200)
S.p.A.		-0.368***	-0.744*	-0.459***
		(0.111)	(0.302)	(0.110)
Coop		-0.00622	-0.0454	-0.118
		(0.0830)	(0.203)	(0.0937)
Consortia		0.434	-0.228	0.174
		(0.297)	(0.479)	(0.285)
Website		0.113***	0.0540	0.0791***
		(0.0180)	(0.0495)	(0.0208)
Log per capita investment, 2020		0.00486	0.00427	
		(0.00251)	(0.00785)	
Log per capita investment in R&D, 2020		0.0127	0.0152	
		(0.00825)	(0.0157)	

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS-CEM	OLS 2019
Log per capita investment in certifications, 2020		0.0330*	0.00232	
		(0.0160)	(0.0372)	
Log per capita investment in IT, 2020		-0.00749	-0.00853	
		(0.00539)	(0.0130)	
Log per capita investment in software, 2020		-0.0164	0.00491	
		(0.00942)	(0.0257)	
Log turnover per capita, 2020		0.00228	-0.00151	
		(0.00417)	(0.0128)	
Log turnover per capita, 2019				-0.0165***
				(0.00451)
Log average income in municipality		-0.544***	-0.911***	-0.619***
		(0.0888)	(0.193)	(0.0966)
Log average rent income in municipality		0.170***	0.0903	0.176***
		(0.0260)	(0.0546)	(0.0282)
Urban		-0.0926**	-0.0766	-0.106**
		(0.0307)	(0.0606)	(0.0352)
Rural		0.0103	0.0123	0.0184
		(0.0238)	(0.0623)	(0.0248)
Mountain		0.185***	0.298***	0.186***
		(0.0311)	(0.0684)	(0.0331)
Beach		0.0639	0.249**	0.0366
		(0.0426)	(0.0854)	(0.0473)
Island		0.192*	0.447	0.164
		(0.0885)	(0.270)	(0.0969)
Coastal		0.0170	-0.144	0.0502
		(0.0421)	(0.0819)	(0.0466)
Population density		-0.0000443***	-0.0000243	-0.0000379**
		(0.0000121)	(0.0000197)	(0.0000128)
North-West		0.0447	0.0559	0.0311
		(0.0347)	(0.0590)	(0.0331)
North-East		0.0637	0.0618	0.0677*
		(0.0328)	(0.0576)	(0.0323)
South and Islands		0.00000316	-0.0466	-0.0194
		(0.0319)	(0.0610)	(0.0326)
Constant	-0.513***	3.306***	7.477***	4.034***
	(0.00871)	(0.870)	(1.817)	(0.934)
Observations	20472	20331	15182	16715
χ^2	34.56	1575.9	555.1	1164.2
R^2	0.000837	0.0468	0.0794	0.0542

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS-CEM	OLS 2019
Log-likelihood	-12737.9	-12069.7	-8472.8	-9882.0

Standard errors in parentheses. Base categories are: Hotels, Individual enterprise, Semi-peripheral municipality, Centre.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.3: Effect of platform adoption on the firm-level share of non-standard employment relationships - Mediating factors - Full table

	(5)	(6)	(7a)	(7b)	(9)
Micro-firms (1-9)	0.229***				
	(0.0476)				
Medium-large firms (50+)	-0.502***				
	(0.0812)				
Multihoming		-0.0677**			
		(0.0262)			
Platform leader			-0.00934	0.156**	
			(0.0502)	(0.0519)	
Platform-related investments					0.0744**
					(0.0274)
Resorts	-0.00217	-0.0338		-0.0606	-0.0255
	(0.122)	(0.119)		(0.122)	(0.121)
B&Bs	-0.233***	-0.272***		-0.192***	-0.279***
	(0.0409)	(0.0402)		(0.0426)	(0.0403)
Restaurants	0.0209	0.0280			0.0382
	(0.0419)	(0.0417)			(0.0422)
Take-aways	0.0812	0.0961	-0.0790		0.102
	(0.0771)	(0.0764)	(0.0672)		(0.0765)
Log rate of turnover change	0.0347***	0.0352***	0.0374**	0.0361***	0.0357***
	(0.00790)	(0.00784)	(0.0143)	(0.00908)	(0.00788)
Log change in personnel	0.259***	0.262***	0.151*	0.329***	0.263***
	(0.0442)	(0.0442)	(0.0629)	(0.0592)	(0.0445)
Log number of employees, 2020	0.307***	0.168***	0.0696**	0.209***	0.161***
	(0.0315)	(0.0185)	(0.0252)	(0.0241)	(0.0184)
Firm age	-0.00215*	-0.00194	-0.00753***	-0.00119	-0.00180
	(0.00102)	(0.00101)	(0.00217)	(0.00118)	(0.00102)
SRL, SAS, SNC	0.219***	0.246***	-0.0341	0.346***	0.241***
	(0.0398)	(0.0397)	(0.0549)	(0.0496)	(0.0397)
S.p.A.	-0.132	-0.172	-0.982***	-0.135	-0.193
	(0.134)	(0.135)	(0.285)	(0.144)	(0.134)
Coop	0.0203	0.0727	-0.152	0.171	0.0712
	(0.168)	(0.166)	(0.289)	(0.198)	(0.167)
Consortia	0.855	0.835		0.887	0.846
	(0.499)	(0.592)		(0.620)	(0.584)
Website	0.124***	0.142***	0.0857	0.150***	0.119***
	(0.0318)	(0.0320)	(0.0450)	(0.0439)	(0.0322)
Log per capita investment, 2020	0.00340	0.00302	-0.000180	0.00403	0.00269

	(1)	(2)	(3)	(4)	(5)
	(0.00399)	(0.00399)	(0.00758)	(0.00459)	(0.00400)
Log per capita investment in R&D, 2020	0.0126	0.0135	0.00808	0.0152	0.0127
	(0.0115)	(0.0115)	(0.0210)	(0.0137)	(0.0116)
Log per capita investment in certifications, 2020	0.0308	0.0290	0.0558	0.0262	0.0287
	(0.0207)	(0.0206)	(0.0310)	(0.0256)	(0.0206)
Log per capita investment in IT, 2020	-0.00428	-0.00533	0.0226	-0.0111	-0.00585
	(0.00864)	(0.00860)	(0.0148)	(0.0104)	(0.00866)
Log per capita investment in software, 2020	-0.0107	-0.00884	-0.0176	-0.0110	-0.0115
	(0.0130)	(0.0129)	(0.0242)	(0.0151)	(0.0130)
Log turnover per capita, 2020	-0.00363	-0.00411	0.000589	-0.00814	-0.00497
	(0.00694)	(0.00691)	(0.0120)	(0.00806)	(0.00688)
Log per capita income in municipality	-0.667***	-0.665***	-0.311	-0.792***	-0.682***
	(0.140)	(0.140)	(0.229)	(0.169)	(0.140)
Log per capita rent income in municipality	0.229***	0.224***	0.108	0.259***	0.220***
	(0.0415)	(0.0416)	(0.0864)	(0.0469)	(0.0412)
Urban	-0.0963	-0.0943	-0.124	-0.0936	-0.105*
	(0.0494)	(0.0492)	(0.0667)	(0.0641)	(0.0498)
Rural	-0.0340	-0.0378	-0.139	-0.0102	-0.0388
	(0.0448)	(0.0449)	(0.0891)	(0.0512)	(0.0449)
Mountain	0.257***	0.250***	0.376***	0.232***	0.259***
	(0.0545)	(0.0546)	(0.109)	(0.0624)	(0.0543)
Beach	-0.0309	-0.0247	-0.000900	-0.0532	-0.0200
	(0.0853)	(0.0854)	(0.158)	(0.0995)	(0.0854)
Island	0.274*	0.273*	0.225	0.231	0.280*
	(0.115)	(0.115)	(0.470)	(0.121)	(0.114)
Coastal	0.0587	0.0541	0.0317	0.0823	0.0536
	(0.0848)	(0.0851)	(0.158)	(0.0997)	(0.0850)
Population density	4.92^{-5}**	-4.94^{-5}**	-3.87^{-5}**	-5.81^{-5}*	-4.99^{-5}**
	(1.87^{-5})	(1.83^{-5})	(1.48^{-5})	(2.89^{-5})	(1.83^{-5})
North-West	0.0604	0.0550	0.0164	0.0531	0.0579
	(0.0466)	(0.0467)	(0.0817)	(0.0559)	(0.0469)
North-East	0.0739	0.0687	0.0351	0.0783	0.0762
	(0.0455)	(0.0458)	(0.0776)	(0.0552)	(0.0463)
South and Islands	0.0593	0.0542	-0.00735	0.0612	0.0509
	(0.0488)	(0.0492)	(0.0864)	(0.0584)	(0.0493)
Constant	3.699**	4.137**	1.953	4.815**	4.255**
	(1.332)	(1.334)	(2.122)	(1.610)	(1.338)
Observations	6830	6830	1622	5208	6830
χ^2	801.5	790.8	123.5	763.4	795.0
R^2	0.0676	0.0653	0.0238	0.0863	0.0653

	(1)	(2)	(3)	(4)	(5)
Log-likelihood	-4063.9	-4073.9	-1012.6	-3034.6	-4073.8

Standard errors in parentheses. Base categories are: Hotels, Individual enterprise, Semi-peripheral municipality, Centre.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.4: Descriptive statistics - Panel data

2019	No platform use	Use of platforms	Total
Observations	13,556 (95.5%)	640 (4.5%)	14,196 (100.0%)
% of non-standard contracts	0.314 (0.359)	0.350 (0.346)	0.316 (0.359)
Firm-level controls			
Log turnover per capita	9.912 (1.847)	9.715 (2.269)	9.903 (1.868)
Subsectors			
Hotels	841	70	911
Resorts	63	3	66
B&Bs	693	62	755
Restaurants	9,996	411	10,407
Take-aways	1,963	94	2,057
Size classes (OECD definition)			
Micro-firms (1-9)	11,581	480	12,061
Small firms (10-49)	1,874	144	2,018
Medium-large firms (50+)	101	16	117
Use of own website	3,003	287	3,290
Geographic controls			
Beach	4,632	279	4,911
Island	121	8	129
Coastal	5,248	290	5,538
Degree of urbanisation			
Urban	3,288	306	3,594
Semi-peripheral	6,310	244	6,554
Rural	3,958	90	4,048
Geographical area of Italy			
North-West	2,846	137	2,983
North-East	3,422	130	3,552
Centre	2,992	149	3,141
South and Islands	4,296	224	4,520
2020			
Observations	13,556 (95.5%)	640 (4.5%)	14,196 (100.0%)
% of non-standard contracts	0.285 (0.353)	0.323 (0.340)	0.287 (0.352)
Firm-level controls			
Log turnover per capita	9.584 (1.945)	9.606 (1.978)	9.585 (1.946)
Subsectors			
Hotels	841	70	911
Resorts	63	3	66
B&Bs	693	62	755
Restaurants	9,996	411	10,407
Take-aways	1,963	94	2,057
Size classes (OECD definition)			

Micro-firms (1-9)	11,581	480	12,061
Small firms (10-49)	1,874	144	2,018
Medium-large firms (50+)	101	16	117
Use of own website	3,003	287	3,290
Geographic controls			
Beach	4,632	279	4,911
Island	121	8	129
Coastal	5,248	290	5,538
Degree of urbanisation			
Urban	3,288	306	3,594
Semi-peripheral	6,310	244	6,554
Rural	3,958	90	4,048
Geographical area of Italy			
North-West	2,846	137	2,983
North-East	3,422	130	3,552
Centre	2,992	149	3,141
South and Islands	4,296	224	4,520
2021			
Observations	13,556 (95.5%)	640 (4.5%)	14,196 (100.0%)
% of non standard contracts	0.304 (0.355)	0.351 (0.342)	0.306 (0.354)
Firm-level controls			
Log turnover per capita	9.615 (2.152)	9.764 (2.034)	9.622 (2.147)
Subsectors			
Hotels	841	70	911
Resorts	63	3	66
B&Bs	693	62	755
Restaurants	9,996	411	10,407
Take-aways	1,963	94	2,057
Size classes (OECD definition)			
Micro-firms (1-9)	11,581	480	12,061
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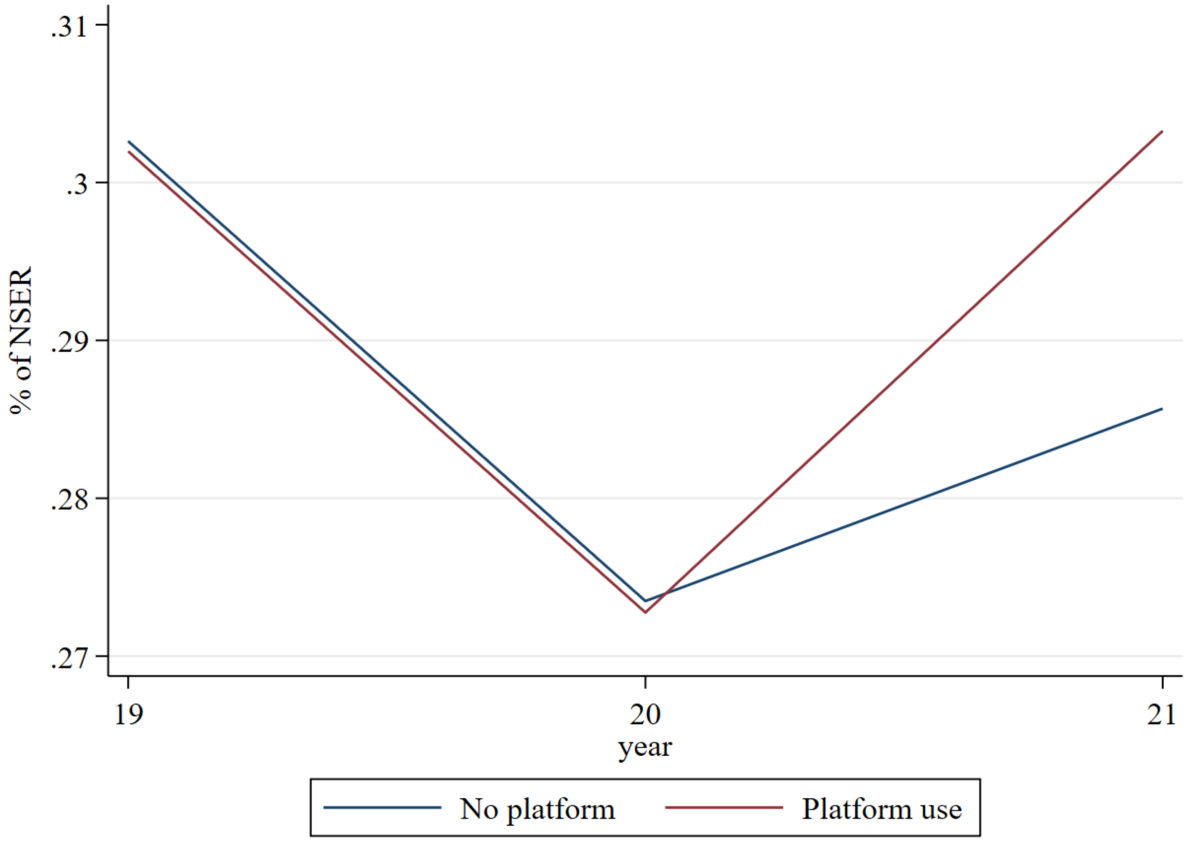
Figures

Figure B.1: Pretrends after CEM matching



Chapter 3

Platform workers, low earnings, and economic insecurity

As the Introduction has discussed, platform power: i) rests on the platform's infrastructural role and on the network effects its intermediation triggers (Coveri et al., 2022); ii) operates over workers and suppliers through algorithmic control and digital monitoring (Vallas et al., 2022); iii) bears on competitors and complementors through disruption, self-preferencing, and the reorganisation of value chains (Khan, 2016; Rahman and Thelen, 2019). Whenever platforms intermediate labour directly, algorithmic control and network effects reinforce one another. Workers are treated as consumers connected through an infrastructure rather than as parties to an employment relationship (Vallas, 2019), and those mediated through labour platforms (henceforth, *platform workers*) are systematically positioned outside the protective scope of subordinate employment. The platform must also elicit labour supply, direct it towards consumers' needs, and ensure conformity to quality standards. These functions are discharged through algorithmic management and digital monitoring, which combine managerial control with the formal flexibility devolved to workers (Wood, 2021). Efficiency gains for the platform coexist with heightened precariousness: as the flexible arrangements typical of platform labour fall at the margins of established regulatory frameworks, they underline unmediated power asymmetries (Bearson et al., 2021; Schor et al., 2020).

The sources of this tension between the flexibility and the precariousness of platform workers are technical, legal, and economic. The technical aspects of the platform's digital applications lower workers' capability of switching, eliciting increasing effort from their part and fostering a perception of instability with respect to earnings, which depend on evaluation task-by-task by customers and algorithms alike (Gregory, 2021; Wood, 2021; Schor et al., 2020).

Platform workers are often legally defined as independent contractors (Aloisi and De Stefano, 2022). This happens despite the approval of the EU Platform Work Directive, which puts platforms through a test to assess subordinate employment, and only recently Italian courts have begun to implement EU laws to reassess the status of platform workers in on-location occupations.[1] The status of platform workers leaves them vulnerable to risks such as illness or injury, and with little guarantee of continuous employment (Aloisi, 2022).

Finally, platforms take advantage of segregation and segmentation in the labour market, as disadvantaged categories of workers enjoy lower bargaining power vis-à-vis the platform (Kumar,

[1] https://tinyurl.com/GlovoCommiss

2020). Worse economic conditions for platform labour vis-à-vis the rest of the population are then also a result of product and labour market organisation (very few platforms in any given industry, large pool of workers).

Two dimensions of platform work deserve special attention. First, platform work is multifaceted: incentive schemes and market structures differ by the type of work performed. Tasks on platforms range from highly complex (freelance software development) to basic online (micro-work) and offline (delivery) ones (De Groen et al., 2018), and certain specificities of tasks may enhance or mitigate the influence of platforms. The relationship of different types of platform work with income and stability may vary accordingly. Second, platform work is unregulated with respect to, *inter alia*, working times. When they do not have access to a stable stream of "gigs", platform workers tend to work fewer hours than the general population. Platforms may purposefully assign a lower number of tasks to workers with lower ranking (those workers refusing tasks and getting bad reviews, Bonifacio (2023); Aloisi and De Stefano (2022)), or not provide a sufficient number of tasks to a worker (because workers are abundant or there is a mismatch in skills or location), yet demand their availability at all times (De Groen et al., 2018; Pulignano et al., 2024). Since there also is no upper limit on the number of hours, platform work may lead to inequality between few workers being overworked and a larger majority not working enough.

Despite its relevance in terms of policy and novelty, there is relatively little evidence concerning the economic conditions of platform workers and their drivers. A problem is in the lack of comprehensive and comparative survey data (Fernández-Macías et al., 2023; Piasna et al., 2022), as well as difficulties in defining what constitutes platform work.

This chapter explores the economic conditions of platform workers vis-à-vis the general population focusing on household income and economic insecurity. It then proposes task heterogeneity and number of hours worked as mechanisms for the transmission of platform work's impacts, exploiting the Italian setting. Italy has in this regard provided a fertile ground for studying platform work, as its productive structure has shifted to services and its labour contracts have become more flexible in recent years (Guarascio et al., 2017; Barbieri and Scherer, 2009). In Italy, statistical offices have devoted special attention to the collection of data related to platform work early on. The country has also been at the forefront of debates regarding platform workers' status as subordinate employees, particularly in the context of food couriers, which resulted in union mobilisations and in decree laws protecting the workers (Marrone et al., 2019). The struggle for recognition has carried on also at the judiciary level, with multiple court orders defining worker status and with the, novel, enforcement of the Platform Work Directive.[2] Italy has also been hit by Covid-19 early on: this chapter also analyses the pandemic's consequences on the relationship between platforms and economic conditions. The 2020 pandemic has become a shift year for food delivery: in 2021, the industry recorded turnovers over 1 billion euros (JustEat, 2021). Platform workers (also intermittent) accounted for 570,000 individuals (Bergamante et al., 2022).

The analysis relies on a unique data source: the Participation, Labour, Unemployment Survey (PLUS) compiled by the Italian Institute for the Analysis of Public Policy. It employs two waves of the survey, 2018 and 2021, each covering 45,000 persons (employed, unemployed, inactive, students, or retired), representative of the Italian population. Both contain a separate module, interviewing a sample of the platform labour force, and a rich set of questions pertaining to working conditions,

[2]https://tinyurl.com/ridercassazione, https://tinyurl.com/GlovoCommiss, https://tinyurl.com/RiderPalermo.

job search, and earnings. Concerning specific platform variables, it has information on different tasks, such as driving, delivery, micro-working, cleaning. For a subset of individuals considering themselves employed, it also contains information on hours worked.

We operationalise income by looking at household income brackets, and economic insecurity by looking at the probability of postponing necessary medical treatment for financial reasons. An ordered probit is employed, including demographic controls, area, year, and area-year fixed effects. As a robustness exercise, we also perform a Coarsened Exact Matching (CEM, Iacus et al. (2012)) on the binary platform variable. Finally, the platform variable is interacted with the year 2021 to assess whether there are differential effects due to the Covid-19 pandemic. The same exercises are repeated with the postponement of necessary medical treatment, using a simple probit methodology. Similarly, a series of platform activities are specified as independent variables. These are driving, merchandise delivery, food delivery, micro-working and other online tasks, and cleaning. Finally, to understand the link between hours worked, platform work, and incomes, we interact a measure of hours worked divided in brackets – less than 20 hours, 20-39 hours, 40 hours, and more than 40 hours – with the dummy for platform work, and use this as the main regressor in both estimations.

Results indicate a correlation between platform work and lower household income brackets. Economic insecurity is higher for platform workers, who postpone necessary medical treatment more often. No significant changes in the relationship between platform work and income follow Covid-19. However, economic insecurity in relation with platform work almost doubles in 2021. Two mechanisms are tested: i) the task composition of platform work, and its changes after Covid, detail varying levels of correlation with worse economic conditions vis-à-vis the population; ii) platform workers have worse outcomes when they work less than 40 hours, and do not enjoy benefits when working more.

The rest of the chapter proceeds as follows: section 3.1 reviews the literature and identifies the relevant gaps, while section 3.2 formulates the research question and ancillary explanatory mechanisms; section 3.3 outlines the data sources, the construction of the variables, and the methods used; section 3.4 comments the results, while Section 3.5 provides a discussion and some implications for policy.

3.1 Literature review and theoretical framework

Digital platforms have long employed workers to deliver goods, connect customers, and perform other services. Despite not employing relatively large numbers of people, platform work has gone from peculiar to paradigmatic: trends in work management that began within the context of platform work have begun to spill over to regular workplaces, at varying extents (use of reviews, monitoring apps, algorithmic decision-making, Fernández-Macías et al. (2023)).

Platform workers account for between 2 and 4 % of the workforce in developed countries, with varying estimates across the United States and Europe (Farrell et al., 2019; Pesole et al., 2018; De Groen et al., 2018; Piasna et al., 2022). Most of these workers perform work on the platform as a side occupation; nonetheless, for Italy the most recent estimates indicate that platforms are the main source of income for 0.9% of total employment (Gonzalez Vàzquez et al., 2025). However marginal, the strategies of algorithmic management and the use of digital monitoring tools involved in the occupations performed by platform workers have become a blueprint for other kinds of jobs

(Gonzalez Vàzquez et al., 2025), so that studying the consequences of platform work has become important to foresee the impacts new technologies and organisational forms will have on other, more traditional forms of work. Platform workers perform several tasks, some online (freelancing, micro-work) and others on location (driving, delivery, other gig work) (Berg et al., 2018), and tend to be slightly better educated and younger (34 years) than the rest of the work-force (Pesole et al., 2018; Urzì Brancati et al., 2019; Martindale and Lehdonvirta, 2023). After the pandemic, the income and education profile of platform workers appears to have realigned with the rest of the population (Piasna et al., 2022; Van Doorn and Vijay, 2024). As vulnerable workers in the informal sector lost their jobs or found themselves unable to perform them because of the restrictions brought upon by the Covid pandemic, they turned to platform work to supplement their income ((Rani and Dhir, 2020; Pirone et al., 2020; Ravenelle et al., 2021)). Competition for tasks increased, sometimes in tandem with platforms lowering payment for certain tasks,[3] benefitting from the conjunction between increased worker competition and consolidated quasi-monopsonistic positions (Fisher, 2024a).

Legal and organisational working conditions for platform workers are different than for the rest of the workforce. In terms of contracts, platform work is still denoted by a general lack of a definition of its status between subordinate employment and independent contracting (Aloisi and De Stefano, 2022; Fernández-Macías et al., 2023).[4] At the same time, platforms afford workers significant flexibility in the performance of most tasks. The result is often one of instability in earnings. The platform dictates earning rates or takes a share of commissions. It then nudges workers to comply with its suggestions through reward systems and the attribution of more and better paid tasks (Bonifacio, 2023; Gregory, 2021; Wood and Lehdonvirta, 2021). Algorithmic management methods in which the platform's algorithms make decisions on routes, tasks and evaluation, stemming from increased task standardisation and codification, are widespread. Customer reviews and ratings result in information the algorithm uses to assign work tasks and incentives (Graham et al., 2017; Wood, 2021; Tubaro and Casilli, 2019; Baiocco et al., 2022; Stark and Pais, 2021). As a result, platform workers experience higher economic insecurity with respect to their non-platform counterparts (Cirillo et al., 2023a), while exerting more effort (Hall and Krueger, 2018). They also engage in competition with more traditional counterparts (i.e., taxi drivers), which then incur in income losses (Abraham et al., 2017). As few platforms dominate most product markets, and enjoy technological and informational advantages over job-seekers, the platform can, for its part, exert monopsony power and decrease platform workers' earnings (Fisher, 2024a).

Most accounts of platform work focus on a just one form of platform work and suffer from sample size and selection issues, with some exceptions (Cirillo et al., 2023a; Urzì Brancati et al., 2019; Piasna et al., 2022; Fernández-Macías et al., 2023; Gonzalez Vàzquez et al., 2025). Recently, better data sources have become available, allowing comparisons with the general population. Surveys such as AIM-WORK (EU Commission) and IPWS (European Trade Union Institute) provide important descriptive evidence. Despite substantial work having been conducted in the field, however, little

[3] https://tinyurl.com/GlovoPagamento.

[4] The implementation of the Platform Work Directive at the Member State level is only recent, and quite patchy: food delivery platforms, for instance, have identified several loopholes allowing them to continue operating in the same manner as they did before; judiciary interventions have opposed limited remedies, yet the reception of the Directive is still due, as integration into national law must be followed, at least in Italy, by executive decrees mandating operational rules. https://tinyurl.com/ridercassazione, https://tinyurl.com/GlovoCommiss.

has been done to better understand the sources of differences in earnings for platform workers. Unstable working arrangements, increasing monopsony power and increasingly reliance on platform work, particularly after the Covid pandemic, are peculiar elements motivating the research question.

3.2 Research question

As the literature review has shown, platform-mediated labour has often been associated with poor working conditions and precariousness. This kind of arrangement can then lead to two main consequences: low pay, and economic insecurity. This paper therefore aims to investigate the income conditions of platform workers, and to understand the relationship that platform work may have with lower income. Relatedly, unstable working arrangements and low income can lead to economic insecurity. Operationalising the probability of postponing medical treatment, which represents a measure of *realised* economic insecurity (Cirillo et al., 2023a), it is possible to measure the relationship between this measure and the condition of platform worker. Clearly, the postponement of medical treatment bore stronger importance during the Covid pandemic, as access to cures was fundamental in the midst of the infection. Understanding whether platform workers differ from the rest of the population more strongly in 2021 with respect to 2018, in income terms but also, more importantly, in economic insecurity becomes then important in two ways: i) to assess the outcomes of the development of the platform economy past its nascent stage ii) to highlight the potential enhanced vulnerability of platform workers.

Once the research question is answered, two potential mechanisms are tested to account for the results.

3.2.1 Mechanisms

First, the task content of platform work has shifted as the platform economy matured. While, at an early stage, platform work was mostly associated with online labour and ride-hailing (Huws et al., 2017; Pesole et al., 2018), it is now widespread as gig delivery work, and has also begun expanding in new industries (Fernández-Macías et al., 2023; Piasna et al., 2022). The relationship of different types of platform work with income and economic insecurity can vary across different platform workers in terms of skills and background. Online labour markets differ markedly in the rewards they post and in the tasks required, as they are polarised between extremely low-skill tasks, such as micro-working, and highly complex ones such as online software development (Garcia Calvo et al., 2023; Tubaro and Casilli, 2020; De Groen et al., 2018). Location platform labour markets, instead, require usually manual low-skill labour, as in food delivery (Berg et al., 2018; De Groen et al., 2018). In Italy, ride-hailing platforms require ownership or rental of a car with certain characteristics, as well as a licence. Competition for gigs between workers similarly varies according to skills, levels of effort, and number of workers available (Bonifacio, 2023; Piasna et al., 2022).

Looking at the development of the industry over time can shed light as to which occupations are becoming more prevalent, and heterogeneities in tasks performed through platforms may provide context as to which platform gigs are more related to economic insecurity. If the most insecure jobs are increasing, then platform work as a whole is becoming more precarious.

The second mechanism concerns hours worked. Most platform workers work less hours than their non-platform counterparts, and earn lower incomes as a result (Fernández-Macías et al., 2023;

Piasna et al., 2022). This is due to the fact that most digital labour platforms allow free access to work: hiring processes are minimal, or non-existent (Aloisi and De Stefano, 2022; Piasna et al., 2022). As the number of workers increases, each worker is allocated less tasks on average, leading to a decrease in hours worked. At the same time, no limitations exist on the number of hours an individual can work on the platform, leading to a minoritarian but significant share of overtime workers (Fernandez Macias et al., 2025; Piasna et al., 2022). A source of significant overtime is represented by idleness between one assigned task and another. Platform workers spend time on the platform and make themselves available for tasks, yet they usually are not paid for it (Pulignano et al., 2024). Only recently court orders in Italy have established a minimum for wait times in front of restaurants, for food delivery couriers.[5]

We then explain the relationship between hours worked, platform work and economic conditions by asking whether lower working hours on platforms are related to lower incomes and higher economic insecurity, and whether longer working hours on platforms lead to better economic conditions.

This study thus aims to contribute to the literature on platform work by documenting platform workers' household incomes vis-à.vis the rest of the population. It will further explain differences in earnings through the mechanisms of skill composition and hours worked provision. It does so by using a unique dataset of Italian workers, described in the next section.

3.3 Data, descriptive statistics, and methodology

The Italian economy provides the setting for this research. This is for three reasons. First, Italian statistical agencies built representative surveys covering platform work. Second, Italy has undergone profound changes in its product and labour market structure (Barbieri and Scherer, 2009) leading to the development of a large low value-added service sector, coupled with increasing share of flexible and non-standard work arrangements, proving to be fertile terrain for the development of the platform economy (Guarascio et al., 2017). A third reason lies in the early conflicts around the status of platform worker that have arisen in Italy, which have put the country at the forefront of the debate on these workers' economic conditions (Marrone et al., 2019).

3.3.1 Data

The analysis draws on variables contained in the Participation, Labour, Unemployment Survey (PLUS) dataset, developed by the National Institute for the Analysis of Public Policy (INAPP) (Bergamante et al., 2022). The PLUS dataset provides detailed information regarding population demographics, work arrangements, unemployment, welfare, behaviours, family needs, and opinions. Since 2018, it features a section dedicated to the platform economy, deriving from product, labour, or capital platforms. Product platforms are used for online sales (Amazon, Vinted). Labour platforms are those which are used to find task-based jobs. Capital platforms involve renting one's house, such as Airbnb. This research focuses on the module concerning online labour platforms, in which workers are asked whether they have earned money online using a platform for labour intermediation, which kind of activities they have performed, and if the income earned is essential, important, or not essential. Two waves of the survey are employed: 2018 and 2021.

[5]See *infra* footnote 4.

3.3.2 Variables

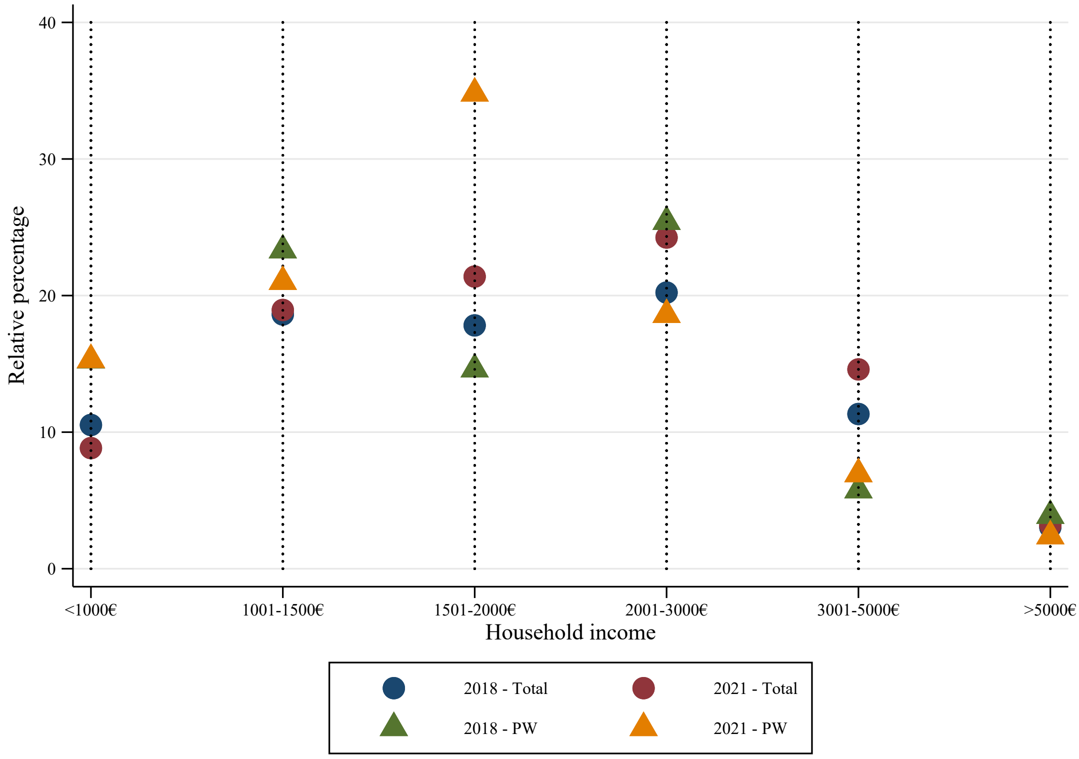
The PLUS dataset employed has 191 variables on population and worker characteristics. For the main sample controls include education, country of birth, number of children, household members, number of breadwinners, a dummy for living in a large urban municipality, and age, plus year, area and area-year fixed effects. The main explanatory variable is a dummy for platform work, simply indicating whether or not the interviewees have performed work on a platform.[6] Roughly half the interviewees report working on a platform, yet identify themselves as unemployed. As a consequence, they are not asked basic questions regarding their wage earnings, which are instead answered by the employed population. We decide to keep all platform workers in the main exercises and employ only those variables stemming from answers given by employed and unemployed interviewees alike. While these are only a subset of all variables, they nonetheless allow a strong comparison on the fundamental characteristics of workers (see Table C.1 in the Appendix) We also conduct split regressions for employed and unemployed individuals so as to include other covariates (Tables C.2, C.3, C.4 and C.5 in the Appendix).

Brackets of monthly household income are the outcome variable (as in Cirillo et al. (2023b)). Since all individuals, regardless of their employment status, report the income earned by their household, the assumption is that, for the unemployed, at least part of that income is obtained through platform work. Since this measure relies on very strong assumptions, controls for employment condition, number of children, number of household members, and number of breadwinners-earners in the household- are always included in regressions. Despite its general nature, not all platform workers answer the question on household income: about a hundred of them does not, thereby reducing our platform worker sample to 602.

Household incomes is available in brackets. Lower incomes are divided in three brackets (less than 1000 €, 1001-1500 €, 1501-2000 €), while middle incomes cover two and high incomes the rest (see Table C.1 in the Appendix). Figure 3.1 shows how the outcome variable behaves across years, and between platform and non-platform workers. In 2021, platform workers appear mostly in the 1501-2000 euro bracket. Working conditions have significantly worsened from 2018, in which the household income of platform workers was mostly concentrated in the 2001-3000 bracket. In both years, platform workers' household income is lower than the general population.

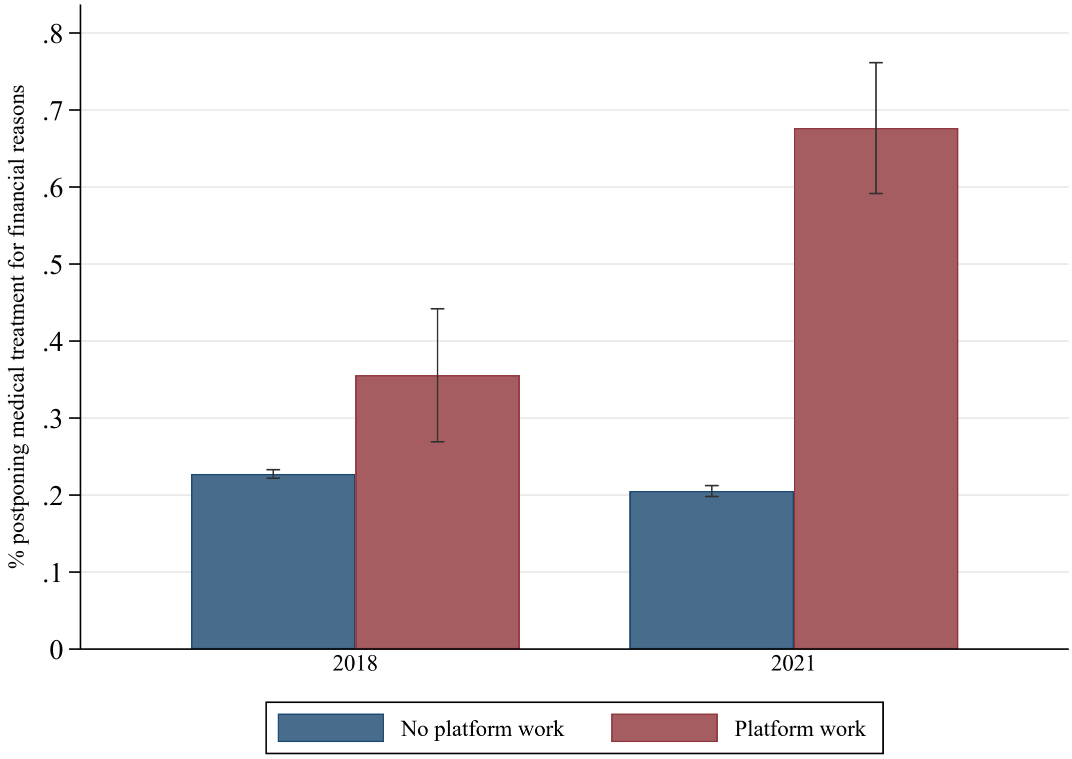
[6] As a robustness check, we also consider only those workers for which platform work income is important or essential. See Tables C.6 and C.7 in the Appendix.

Figure 3.1: Changes in household income distribution across years and categories of workers



We also aim to assess the economic conditions of platform workers in terms of economic insecurity, the consequences of low incomes and increased job precariousness. Economic insecurity is proxied by observing the probability of postponing medical treatment for financial reasons. This is a better measure than forward-looking alternatives (stemming from questions asking the amount of sudden expenses that individuals would be able to meet with their own resources) because it addresses realised economic insecurity, and is not dependent on expectations (Cirillo et al., 2023a).

Figure 3.2: Percent of individuals postponing medical treatment across years and categories of workers

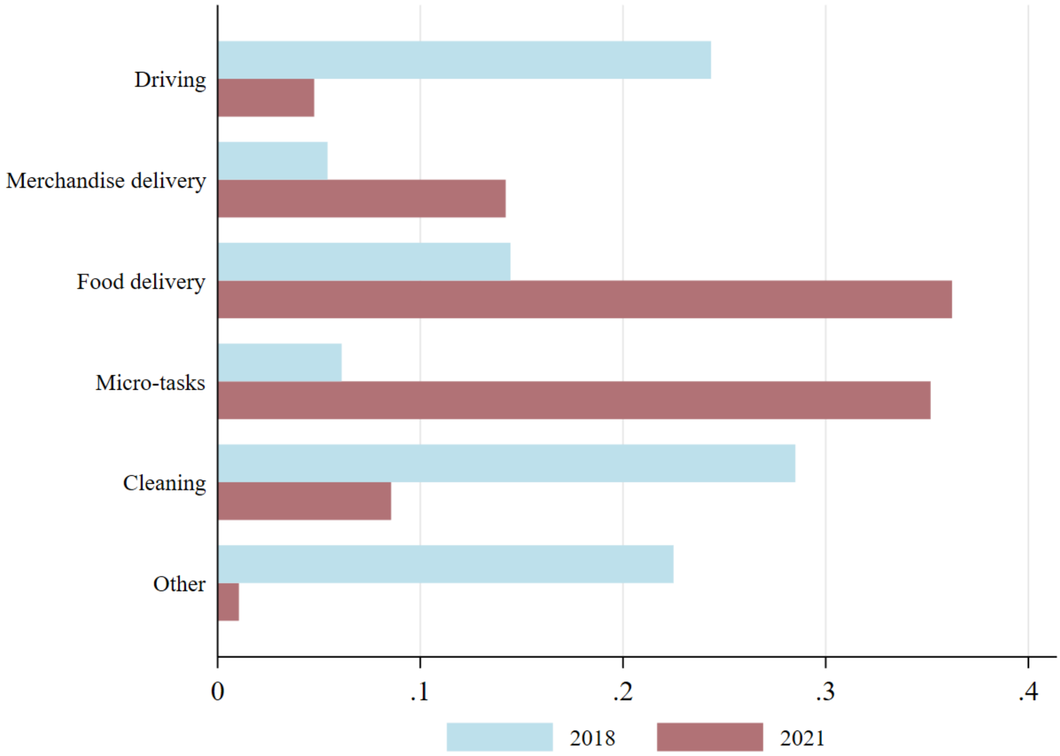


From Figure 3.2, it is possible to observe that the difference between the two categories is marked. Platform workers were more likely to have postponed medical treatment in 2018. This likelihood doubles in 2021, showing that economic insecurity has increased, possibly in relation with the Covid pandemic. Platform workers thus appear as more vulnerable than the rest of the population.

Platform tasks differ strongly. The PLUS dataset allows to explore this heterogeneity by asking platform workers their type of platform gig. Jobs can be driver, merchandise delivery worker, food courier, micro-worker/online worker, cleaner, or other. Drivers work for ride-hailing platforms such as Uber; merchandise delivery workers deliver products for platform such as Glovo and TakeMy-Things; food delivery workers work for platforms such as JustEat and Deliveroo, transporting meals from restaurants to customers; micro-workers and online freelancers are grouped under the same category, but the first kind of worker completes basic tasks on platforms such as Amazon Mechanical Turk, while freelancers usual seek jobs on platforms such as Upwork and Fiverr. Cleaners finally are mediated through platforms such as ProntoPro or Yoopies (Giuliani and Paraciani, 2024).

Over the period, the share of platform workers in the sample has doubled. In Figure 3.3 it's possible to observe that the platform workforce composition leans more heavily towards micro- and online tasks and delivery work in 2021 with respect to 2018. This shift in the tasks performed reflects the influence of the Covid pandemic: platform workers perform tasks related to staying at home: micro-working (performed at home) and delivery (necessary for other people to stay home). In turn, if these tasks are less paying with respect to tasks such as driving (ride-hailing), this shift could help explain the observed difference in household incomes.

Figure 3.3: Variation in platform worker tasks across years

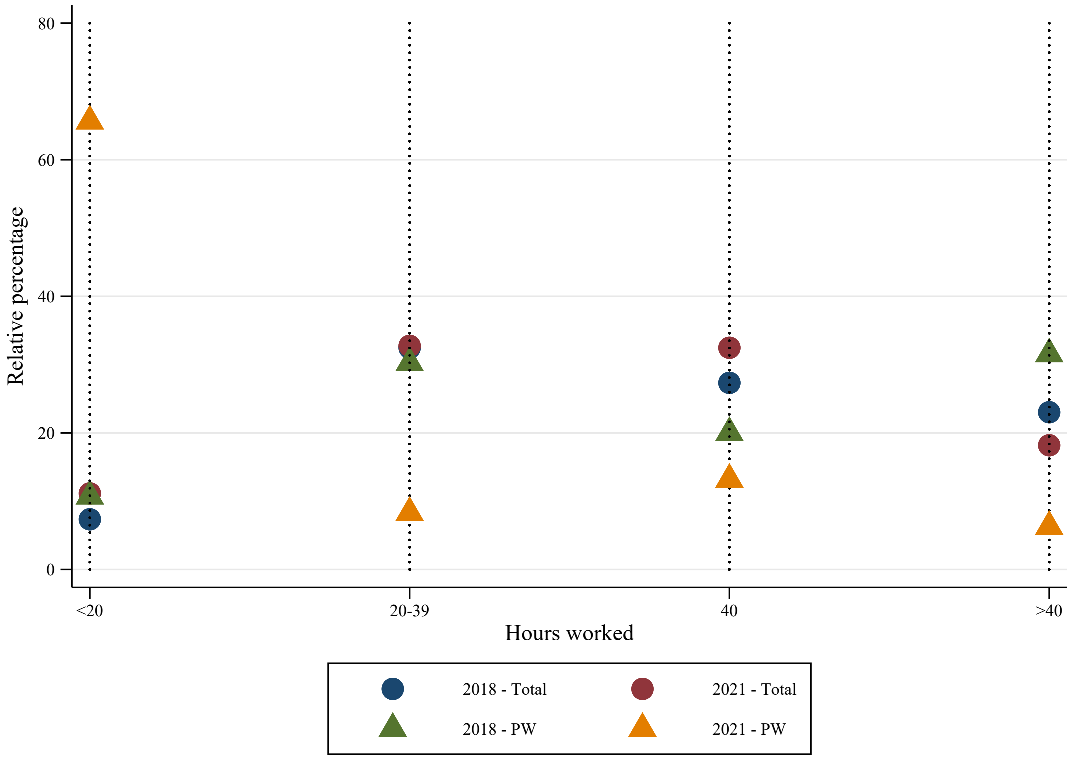


Micro-work and food delivery are usually less well-remunerated than other types of jobs which command higher rewards, require investment by the worker, or more complex skills. Therefore, we aim to validate whether or not their increasing presence among platform workers leads to lower household incomes. Similarly, economic insecurity can be more prevalent for tasks such as micro-work, in which the competition is often global and employers can switch easily between workers (Tubaro and Casilli, 2020; Kassem, 2022).

Finally, the PLUS dataset splits early on between employed individuals and unemployed, or inactive, ones. Most importantly, hours worked are available only for the employed population. They are therefore employed to validate our hypothesis that platform work is linked to fewer hours, in turn leading to lower household incomes.

When observing hours worked, a noticeable peak emerges around 40 hours - which are the average weekly workload in the Italian private sector. Therefore, Figure 3.4 displays hours worked in four categories, ranging from less than 20 to more than 40. A first, descriptive evidence confirming the hypothesis of lower working hours concerns platform workers in 2021, as many work less than 20 hours per week.

Figure 3.4: Hours worked, in categories, across years and categories of workers



In the next section, we review the methods employed to analyse the main relationship between income and platform work and the mechanisms associated with lower household incomes and higher economic insecurity.

3.3.3 Econometric strategy

To address the research question, related to platform workers' incomes, we rely on the following strategy. The outcome of interest is household income, distributed in ordered brackets. The main challenge faced in estimation has to do with the latent nature of the real response of individuals. Thus, we estimate an ordered probit, to assess the probability of moving from a bracket to another depending on a set of covariates, of which platform work represents the central independent variable of interest.

To strengthen the interpretation of our results, we include the demographic controls listed in Table C.1.

The main equation reads as follows:

$$\Phi_i = \alpha + \beta_1 plat_i + \sum_{k=1}^{K} \beta_k X_i + \gamma_g + \theta_t + \gamma_g \times \theta_t + \varepsilon_i \tag{3.1}$$

Φ is the set of observable characteristics in the estimation of the standard normal cumulative density function F, contributing to estimate probability p:
$p_{ij} = p(y_i = j) = p(a_{j-1} < y^* < a_j) = F(a_j - \Phi_i'\beta) - F(a_{j-1} - \Phi_i'\beta)$.

p_{ij} is the probability for individual i of crossing a threshold j; y^* is the real, unobserved household income of individual i, between thresholds $a_0, ..., a_{j-1}, a_j, a_{j+1}, ..., a_J$; $plat_i$ is the dummy for platform work, X_i are controls at the individual level (see Table C.1), γ and θ are area and year fixed effects, respectively, while ε is an error term.

To retrieve estimates robust to self-selection, this equation is repeated on a common support obtained by a Coarsened Exact Matching (Iacus et al., 2012) on the following covariates: education, country of birth, number of children, household members, number of breadwinners, a dummy for living in a city, age brackets, area, and year. While this does not address endogeneity issues completely (such as omitted variable bias), it represents an advancement towards a more precise interpretation of the estimates' chain of events, particularly when coupled with the richness of the controls applied.

Finally, aiming to understand whether the relationship between platform work and incomes changes significantly after the pandemic, an interaction term between the year 2021 and the platform dummy is introduced into Equation 3.1.

Turning to economic insecurity, we follow Cirillo et al. (2023a) and implement a probit estimate using the same controls as Equation 3.1.

$$P(Insec_i) = \alpha + \beta_1 plat_i + \sum_{k=1}^{K} \beta_k x_i + \gamma_g + \theta_t + \gamma_g \times \theta_t + \varepsilon_i \tag{3.2}$$

where $Insec_i$ is a dummy equal to 1 for having postponed necessary medical treatment for financial reason in the previous year, x_i are controls at the individual level (see Table A.1), γ and θ are area and year fixed effects, respectively, while ε is an error term. We also similarly include a CEM estimation, and an estimation using an interaction term with year 2021.

A second set of regressions examines the role of different tasks within platform work, keeping non-platform workers as a baseline category:

$$\Phi_i = \alpha + \sum_{h=1}^{H} \beta_h task_i + \sum_{k=1}^{K} \beta_k X_i + \gamma_g + \theta_t + \gamma_g \times \theta_t + \varepsilon. \tag{3.3}$$

where

$task = \{none, driving, delivery, food, microwork, cleaning, other\}$.

The equation's design reflects the fact that an individual may perform more than one platform tasks. *none* is the base level, representing individuals not performing platform work; *driving* includes platform workers for Uber and similar ride-hailing platforms; *delivery* concerns the delivery of products of any kind, through platforms such as Glovo and TakeMyThings; $food$ focuses on food delivery platforms such as Deliveroo and JustEat, *microwork* deals with online platforms such as Amazon Mechanical Turk, *cleaning* refers to platforms for household help, and *other* is a miscellaneous item.

We also aim to estimate the relationship between varying platform tasks and economic insecurity, thus estimating a probit equation:

$$P(Insec_i) = \alpha + \sum_{h=1}^{H} \beta_h task_i + \sum_{k=1}^{K} \beta_k x_i + \gamma_g + \theta_t + \gamma_g \times \theta_t + \varepsilon_i \tag{3.4}$$

where
$task = \{none, driving, delivery, food, microwork, other\}$.

$Insec_i$ is a dummy equal to 1 for having postponed necessary medical treatment for financial reason in the previous year, x_i are controls at the individual level, γ and θ are area and year fixed effects, respectively, while ε is an error term.

For all equations mentioned above, we also calculate the marginal effects[7] of being a platform worker, reported graphically.

As a last exercise, we wish to estimate whether or not the correlation of platform work with household income is driven by differences in hours worked. Hours worked are available only for employed persons: among them, 365 are platform workers.

We interact platform work with a qualitatively chosen measure of hours worked, observable also in Figure 3.4. The measure was chosen based on the fact that the average work week, for the Italian private sector, is made of 40 hours. Hence, a part-time is usually around 20 hours. Therefore the measure considers workers under 20 hours, who probably work intermittently, those between 20 and 40 hours (part-time work), those working exactly 40 hours (the baseline) and those working more than 40 hours a week. This measure is then interacted with the platform work dummy, and presented using the "No platform, 40 hours a week" category as a baseline.

$$\Phi_i = \alpha + \beta_1 plat_i \times hours_i + \sum_{k=1}^{K} \beta_k X_i + \gamma_g + \theta_t + \gamma_g \times \theta_t + \varepsilon_i \tag{3.5}$$

where $hours = \{< 20, 20 - 40, 40, > 40\}$.

The exercise is repeated with the probability of having postponed necessary medical treatment.

$$P(Insec_i) = \alpha + \beta_1 plat_i \times hours_i + \sum_{k=1}^{K} \beta_k x_i + \gamma_g + \theta_t + \gamma_g \times \theta_t + \varepsilon_i \tag{3.6}$$

where $hours = \{< 20, 20 - 40, 40, > 40\}$.

The next section outlines the results.

3.4 Results

3.4.1 Platform work, household income, and economic insecurity

Table 3.1 illustrates the results of the ordered probit estimates. Performing platform work is negatively associated with household income. This implies that a platform worker is more likely to move downward the scale of possible income brackets. Calculating marginal effects shows that platform work is associated with a 5% increase in the probability of falling within the 1001-1500 income bracket (Figure 3.5a), and 4% more likely to be in the bracket earning less than 1000 euros. The finding holds also when controlling for self-selection (Figure 3.5b) through a Coarsened Exact Matching, although with a lower mean coefficient and wider confidence bands. The Covid pandemic does not seem to have influenced significantly the results (Model 4).

[7] $\delta p_{ij}/\delta plat_i = \{F'(a_{j-1} - \Phi'\beta) - F'(a_j - \Phi'\beta)\}\beta_r$ and $plat_i = \{0, 1\}$.

Table 3.1: The relationship between platform work and household income - Ordered probit estimates

	(1) OP	(2) OP	(3) OP-CEM	(4) OP-2021
Platform work	-0.336***	-0.341***	-0.156*	-0.227**
	(0.0402)	(0.0421)	(0.0673)	(0.0759)
PW×2021				-0.164
				(0.0911)
Controls	NO	YES	YES	YES
Area FE	NO	YES	YES	YES
Year FE	NO	YES	YES	NO
Area×Year FE	NO	NO	YES	YES
Observations	78885	77238	4522	77238
Pseudo-R^2	0.000267	0.125	0.113	0.124
Log-likelihood	-131599.3	-112176.0	-6480.6	-112218.5
χ^2	70.19	31947.0	524.8	31862.0

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, number of breadwinners in the household, residence in a 250k+ city, employment status, sex, age.

Figure 3.5a: Marginal effects of platform work on household income, after an ordered probit estimation

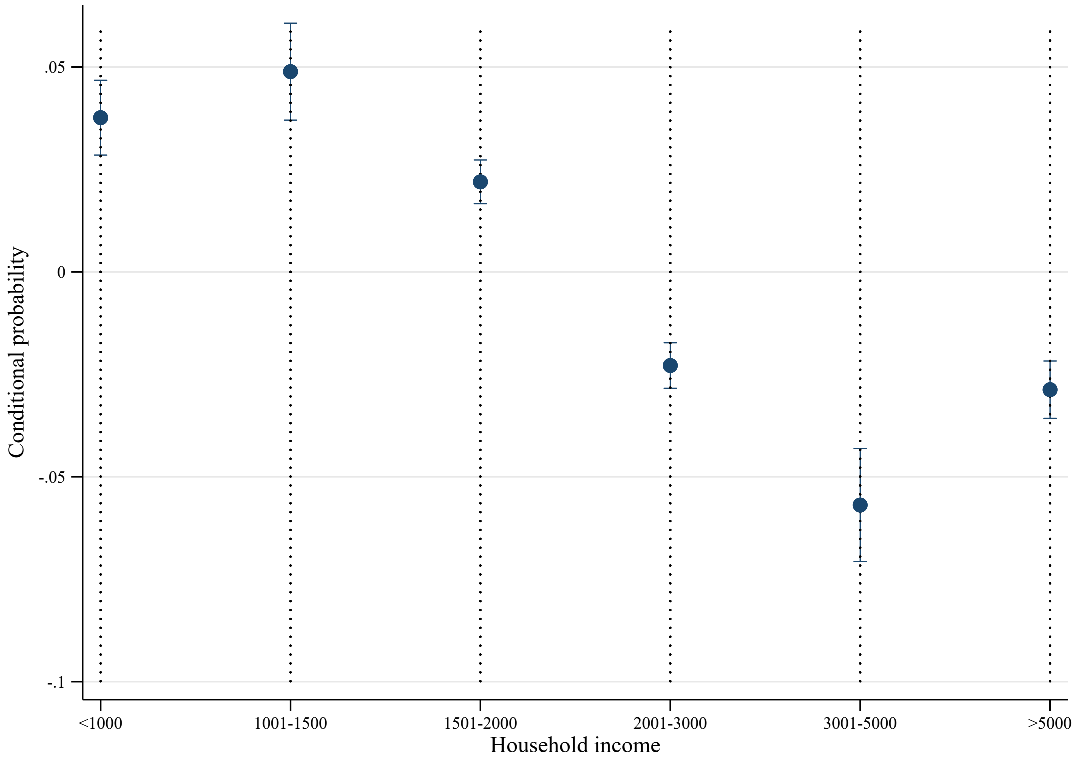
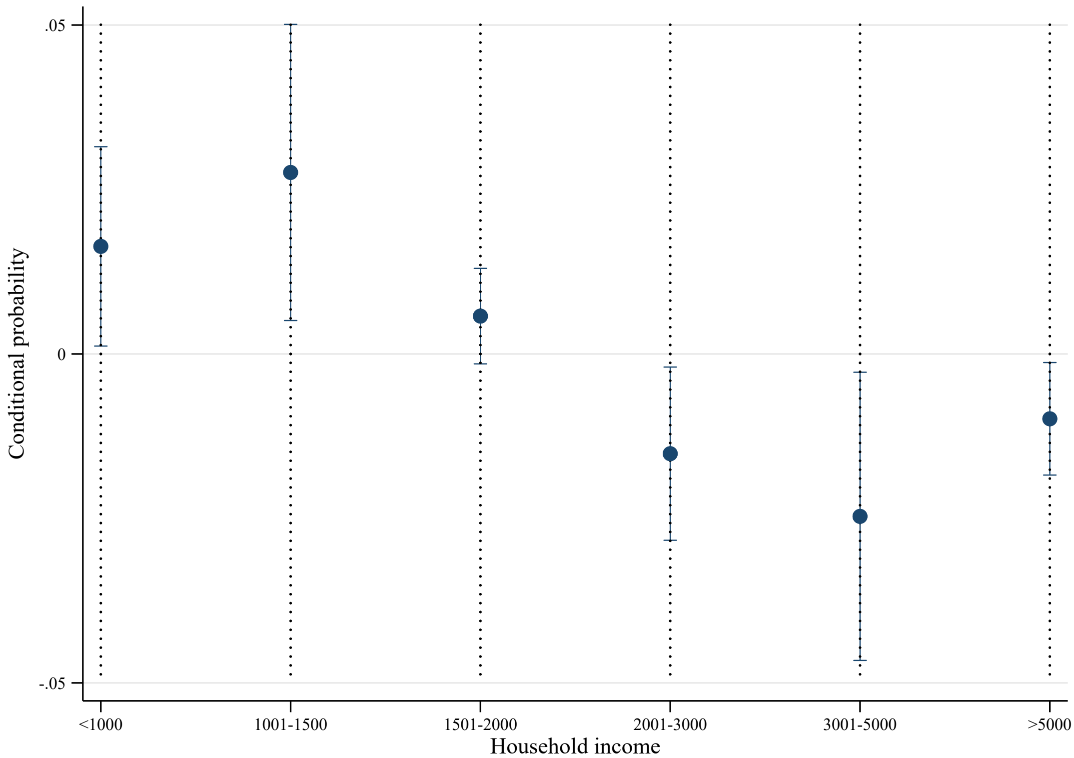


Figure 3.5b: Marginal effects of platform work on household income, Coarsened Exact Matching ordered probit estimates



From these estimates, it is possible to establish that platform work bears a strong relation with poorer working conditions, leading to lower incomes.

This translates in higher levels of economic insecurity. Probit estimates (Table 3.2) show that platform work is consistently associated with having postponed necessary medical treatment. In this case, also the interaction with year 2021 shows that economic insecurity associated with platform work has increased after Covid. This highlights how platform workers were employed in more high-risk occupations and were thus more vulnerable to diseases and injuries, generating an increased correlation of this type of work with economic insecurity.

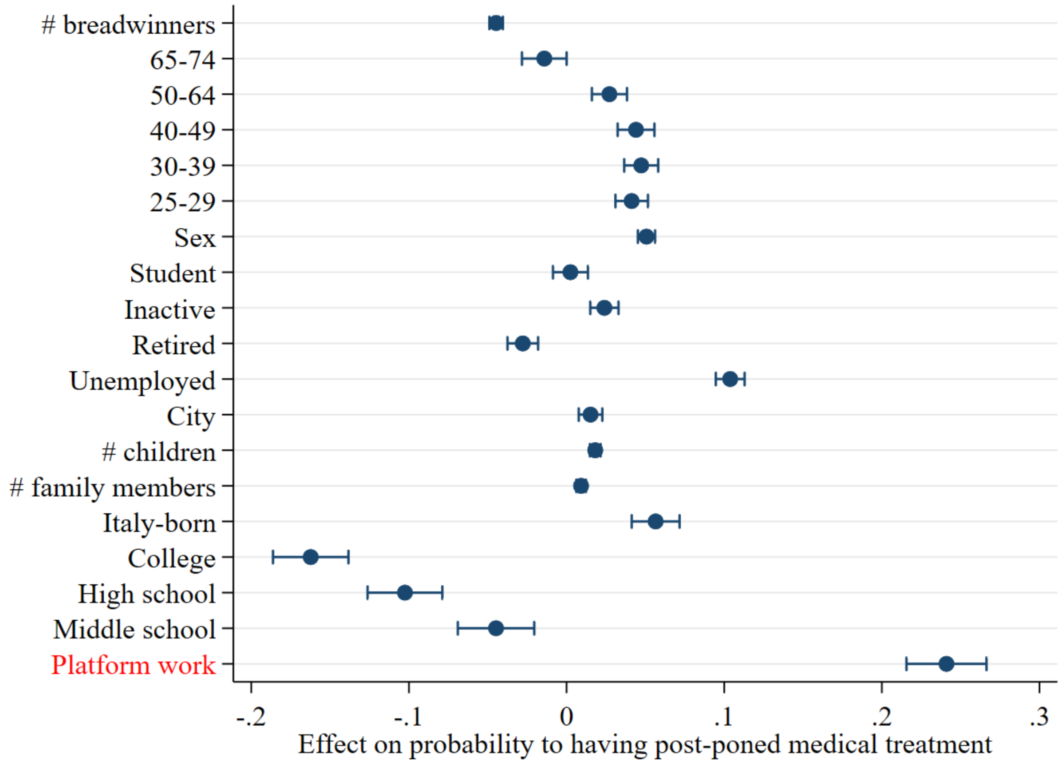
To understand the main mechanisms through which these outcomes arise, two hypotheses are tested.

Table 3.2: The relationship between platform work and the probability of postponing necessary medical treatment

	(1) Probit	(2) Probit	(3) CEM	(4) 2021
Platform work	0.949***	0.928***	0.703***	0.409***
	(0.0475)	(0.0501)	(0.0864)	(0.0895)
PW×2021				0.770***
				(0.109)
Controls	NO	YES	YES	YES
Area FE	NO	YES	YES	YES
Year FE	NO	YES	YES	NO
Area×Year FE	NO	YES	YES	NO
Constant	-0.828***	-0.848***	-0.376	-0.796***
	(0.00473)	(0.0476)	(0.378)	(0.0460)
Observations	91219	89219	5141	89219
Pseudo-R^2	0.00431	0.0758	0.161	0.0751
Log-likelihood	-46260.5	-41567.9	-2607.2	-41595.5
χ^2	400.2	6814.2	347.7	6759.0

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, number of breadwinners in the household, residence in a 250k+ city, employment status, sex, age.

Figure 3.6: Marginal effects of platform work on the probability of having postponed necessary medical treatment, probit estimates



3.4.2 Heterogeneity in platform tasks

The first mechanism relates to changes in the task composition of platform work. Using non-platform workers as a base category, it is possible to decompose platform work in different jobs performed on platforms. In Table 3.3, ordered probit estimates show an association between food delivery, micro-work, cleaning, and lower incomes. As Figure 3.3 showed, in 2021 food delivery became relatively more relevant, as did micro-working. Marginal effects show that the relationships vary between tasks.

Table 3.3: The role of different platform tasks on household income

	(1)	(2)
	OP	OP
Driving	-0.0593	0.0307
	(0.131)	(0.134)
Merchandise delivery	-0.289*	-0.229
	(0.118)	(0.123)
Food delivery	-0.243***	-0.270***
	(0.0728)	(0.0767)
Micro-work	-0.410***	-0.480***
	(0.0744)	(0.0784)
Cleaning	-0.472***	-0.451***

Table 3.3: The role of different platform tasks on household income

	(1)	(2)
	OP	OP
	(0.115)	(0.120)
Other	-0.442***	-0.310*
	(0.126)	(0.128)
Controls	NO	YES
Area FE	NO	YES
Year FE	NO	YES
Area×Year FE	NO	YES
Observations	78885	77238
Pseudo-R^2	0.000305	0.125
Log-likelihood	-131594.2	-112171.1
χ^2	80.32	31956.8

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, number of breadwinners in the household, residence in a 250k+ city, employment status, sex, age.

Driving and merchandise delivery do not show significant change from a non-platform baseline. Platform work in food delivery is associated positively with lower incomes. The two strongest associations with lower income brackets are those of micro-work and cleaning. Two different explanations must be given for these results: in the first case, micro-work is scarcely protected by employment laws, and the competition for online tasks is global, leading to depressed compensation (Kassem, 2022); in the second case, a gender dimension could explain the result, as cleaning services are often performed by (migrant) women who are structurally less paid than their (native) male counterparts (Giuliani and Paraciani, 2024; Bonifacio and Pais, 2025).

This evidence points to the fact that the negative relationship between platform work and lower incomes is driven in part by the task heterogeneity within platform work. Task heterogeneity plays a role also in the level of experienced economic insecurity. Within different platform tasks, food delivery couriers are the ones most likely to postpone necessary medical treatment for financial reasons (Figure 3.8). However, only driving for an app displays non-significance with respect to this outcome variable, pointing to a general nature of platform work leading to higher insecurity, such as the extreme flexibility/precariousness and the absence of subordinate contracts.

Table 3.4: The relationship between different platform tasks and the probability of postponing necessary medical treatment

	(1)	(2)
	Probit	Probit
Driving	0.201	0.256

Table 3.4: The relationship between different platform tasks and the probability of postponing necessary medical treatment

	(1)	(2)
	Probit	Probit
	(0.163)	(0.170)
Merchandise delivery	0.988***	0.905***
	(0.139)	(0.144)
Food delivery	1.125***	1.159***
	(0.0887)	(0.0944)
Micro-work	1.026***	1.024***
	(0.0900)	(0.0950)
Cleaning	0.867***	0.714***
	(0.136)	(0.144)
Other	0.605***	0.499**
	(0.156)	(0.161)
No answer	0.223	0.167
	(0.404)	(0.420)
Controls	NO	YES
Area FE	NO	YES
Year FE	NO	YES
Area×Year FE	NO	YES
Constant	-0.828***	-0.808***
	(0.00473)	(0.0533)
Observations	91219	89219
Pseudo-R^2	0.00454	0.0760
Log-likelihood	-46249.6	-41558.5
χ^2	422.1	6832.9

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, number of breadwinners in the household, residence in a 250k+ city, employment status, sex, age.

3.4.3 Platform work and hours worked

As a last exercise, we analyse the relationship between platform work and hours worked, on a subset of employed individuals. Results indicate that, compared with a population working less than 20 hours a week, platform workers under 20 hours have lower household incomes (Table 3.5). Conversely, when platform workers work more than 40 hours a week, they see no benefit in terms of incomes, contrary to their non-platform counterparts. This result can be interpreted as partial

Figure 3.7: Marginal effects of different platform work tasks on household income, after an ordered probit estimation

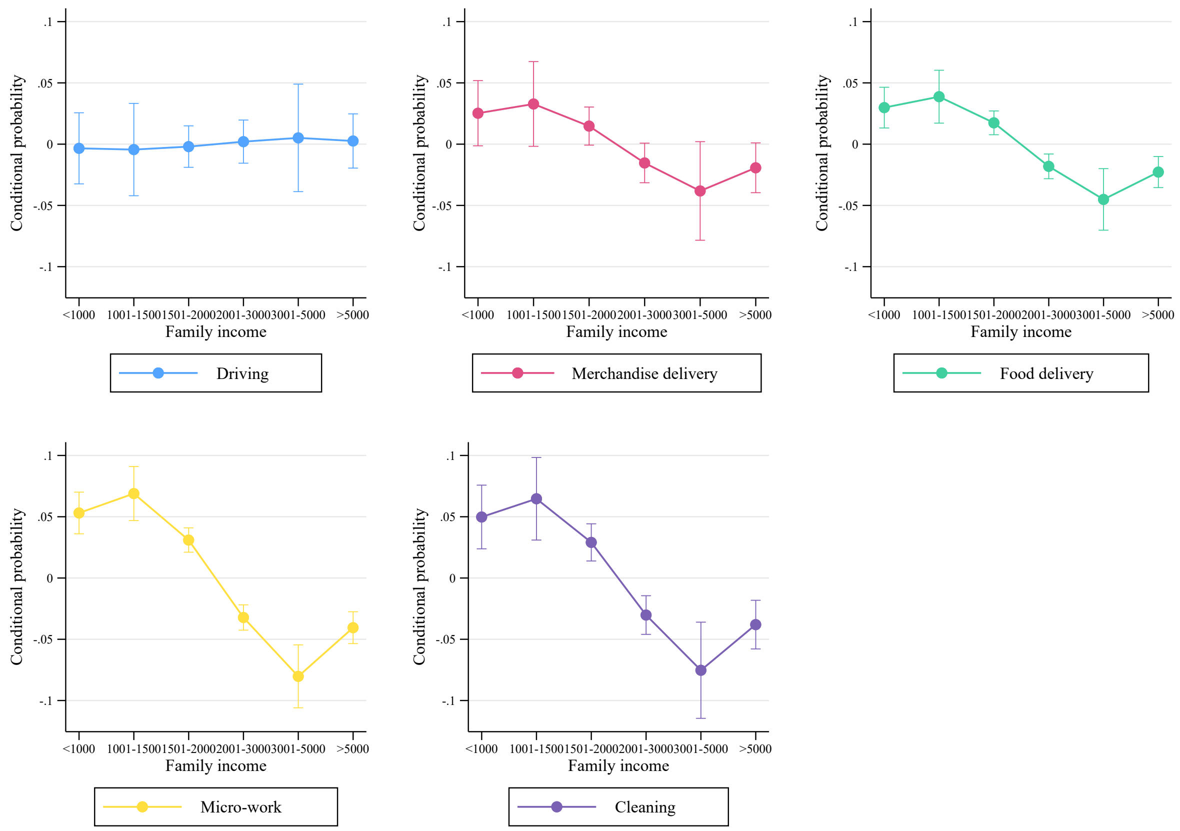
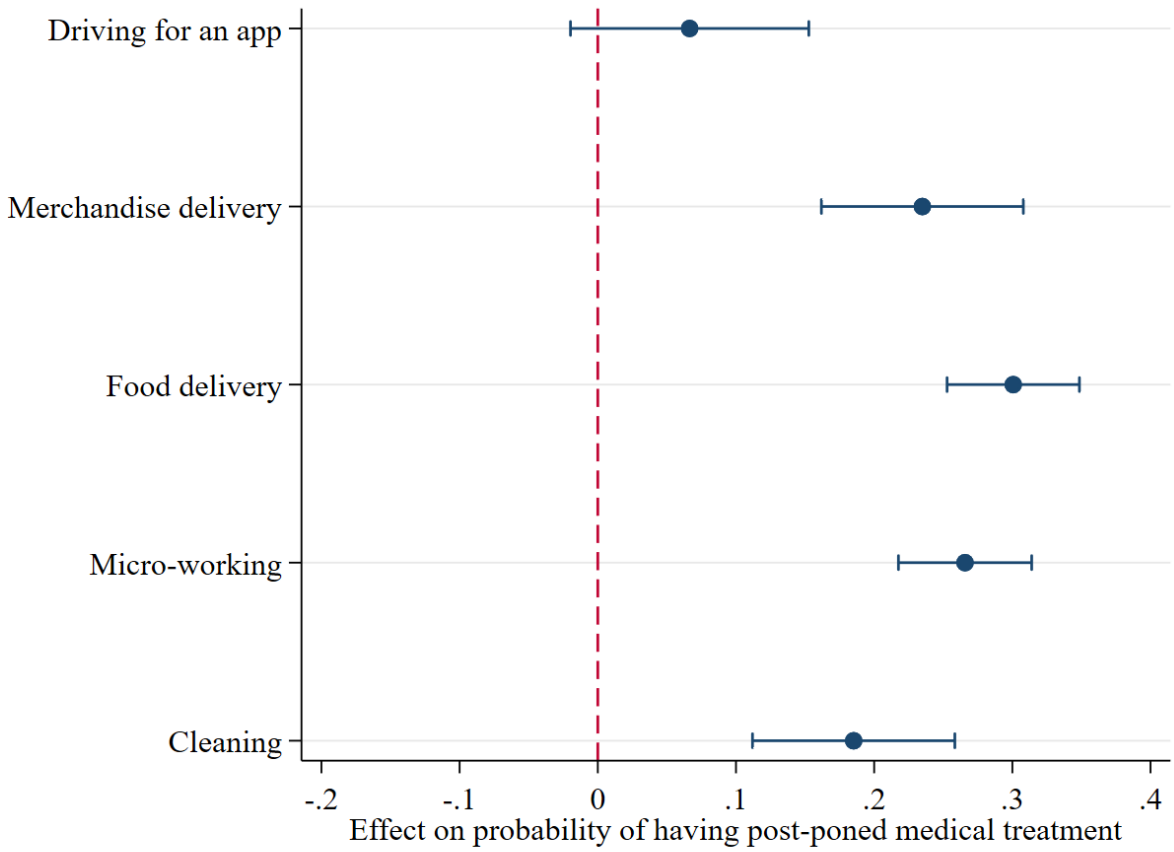


Figure 3.8: Marginal effects of different platform work tasks on economic insecurity, after a probit estimation



evidence of idleness during working hours, driven by unpaid waiting times between piece-rate tasks, which platform workers frequently experience (Pulignano et al., 2024). Interestingly, the share of workers doing platform work and working between 20 and 40 hours a week do not witness lower household incomes, while those workers under other working arrangements do: potentially, this reflects the share of platform workers which perform platform work as a supplement to other part-time jobs.

As for the impact of Covid in shaping platform work, a separate regression shows that little difference exists between platform and non-platform workers working less than 20 hours a week in 2021. However, a significant difference exists between those working more than 40 hours a week (overtime) in regular jobs, and those doing overtime within platforms.

Table 3.5: Platform work-hours worked interaction and household income

	(1)	(2)	(3)
	OP	OP	OP-2021
Less than 20 hours a week ×No PW	-0.357***	-0.478***	
	(0.0219)	(0.0228)	
Less than 20 hours a week ×PW	-0.708***	-0.620***	
	(0.0815)	(0.0828)	
Between 20 and 40 hours a week ×No PW	-0.0751***	-0.117***	
	(0.0140)	(0.0147)	
Between 20 and 40 hours a week ×PW	-0.229	-0.262*	
	(0.131)	(0.133)	
40 hours a week ×No PW	Baseline		
40 hours a week ×PW	-0.260	-0.256	
	(0.145)	(0.147)	
More than 40 hours a week ×No PW	0.147***	0.110***	
	(0.0167)	(0.0173)	
More than 40 hours a week ×PW	-0.226	-0.241	
	(0.150)	(0.152)	
Less than 20 hours a week ×No PW×2021			-0.619***
			(0.0314)
Less than 20 hours a week ×PW×2021			-0.650***
			(0.0855)
Between 20 and 40 hours a week ×No PW×2021			-0.157***
			(0.0195)
20 and 40 hours a week ×PW×2021			-0.232
			(0.161)
40 hours a week ×No PW×2021			Baseline

40 hours a week ×PW×2021			-0.230
			(0.174)
More than 40 hours a week ×No PW×2021			0.0952***
			(0.0246)
More than 40 hours a week ×PW×2021			-0.446*
			(0.198)
Controls	NO	YES	YES
Area FE	NO	YES	YES
Year FE	NO	YES	NO
Area×Year FE	NO	YES	NO
Observations	31274	31274	31274
Pseudo-R^2	0.00562	0.101	0.101
Log-likelihood	-49991.3	-45209.4	-45185.4
χ^2	565.1	10129.1	10177.0

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, number of breadwinners in the household, residence in a 250k+ city, employment status, sex, age.

Turning to our measure of economic insecurity provides further clarity in the interpretation of the estimates. Platform workers are, across different brackets of working hours, consistently more likely to have postponed medical treatment for financial reasons. The contribution to this likelihood declines as hours increase, as would be expected. Yet, platform workers working more than 40 hours a week are three times as likely to have postponed as non-platform workers working under 20 hours.

Table 3.6: Platform work-hours worked interaction and the probability of postponing necessary medical treatment

	(1) Probit	(2) Probit	(3) 2021
Less than 20 hours a week ×No PW	0.272***	0.210***	
	(0.0287)	(0.0301)	
Less than 20 hours a week ×PW	2.096***	2.050***	
	(0.119)	(0.122)	
Between 20 and 40 hours a week ×No PW	0.135***	0.0676***	
	(0.0194)	(0.0205)	
Between 20 and 40 hours a week ×PW	0.985***	0.977***	
	(0.155)	(0.158)	
40 hours a week ×No PW	Baseline		
40 hours a week ×PW	0.634***	0.659***	

	(1)	(2)	(3)
	(0.180)	(0.179)	
More than 40 hours a week ×No PW	0.0411	0.0531*	
	(0.0234)	(0.0244)	
More than 40 hours a week ×PW	0.592**	0.591**	
	(0.188)	(0.194)	
Less than 20 hours a week ×No PW×2021			0.210***
			(0.0420)
Less than 20 hours a week ×PW×2021			2.140***
			(0.130)
Between 20 and 40 hours a week ×No PW×2021			0.0543
			(0.0277)
Between 20 and 40 hours a week ×PW×2021			1.053***
			(0.195)
40 hours a week ×No PW×2021			Baseline
40 hours a week ×PW×2021			0.652**
			(0.215)
More than 40 hours a week ×No PW×2021			0.0807*
			(0.0352)
More than 40 hours a week ×PW×2021			0.544*
			(0.256)
Controls	NO	YES	YES
Area FE	NO	YES	YES
Year FE	NO	YES	NO
Area×Year FE	NO	YES	NO
Constant	-1.099***	-0.871***	-0.870***
	(0.0144)	(0.169)	(0.170)
Observations	35807	35807	35807
Pseudo-R^2	0.0168	0.0591	0.0594
Log-likelihood	-15476.4	-14811.0	-14806.5
χ^2	530.1	1860.8	1869.7

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, number of breadwinners in the household, residence in a 250k+ city, employment status, sex, age.

In 2021, platform work is associated with a much higher probability of postponing medical treatment. It would appear that, after the Covid pandemic, the relationship between the two variables became stronger in magnitude.

From these estimates, working hours appear to be a promising channel for the explanation of how platform work generates economic insecurity and lower household incomes. Platforms appear to provide generally insufficient working hours.

3.4.4 Robustness checks

Three robustness checks are performed. The first two deal with the extensions of the available controls. The third one distinguishes between essential and non-essential platform work.

First, since the PLUS survey splits early on in two sets of questions asked separately to the employed and the unemployed, restricting the sample allows us to make comparisons on a wider set of covariates. For employed individuals, controls include firm size (thus also platform firm size), union status, working conditions (overtime, nightwork, holiday work, risk-proneness, contract presence, part-time contract), opinions on work satisfaction and workplace innovation, workplace firing behaviour, previous contract type and job search duration in months. This allows to better characterise the relationship between platform work and incomes as peculiar to the former in terms of work organisation and algorithmic management. When considering employed individuals, a number of characteristics related to their working conditions can be included in the regression. Platform work does, of course, influence working conditions (Wood, 2021; Baiocco et al., 2022). Therefore, accounting for them in different items (night-time work, overtime, holiday work, type of contract) leads to the estimation of the relationship between platform work and income earned when considering similar types of work being performed. Further, the industrial sector of the worker is accounted for. In Table C.2 in the Appendix, the negative association is confirmed, with results that are similar in magnitude to Table 3.1. Similarly to the general estimation, platform work ceases to be significantly associated with household income when interacted with the year 2021, showing that, for employed persons performing platform work, no significant change was present between the pre- and post-Covid years. Concerning economic insecurity, for employed individuals the probability to postpone necessary medical treatment in relation with platform work is higher, confirming the general results. This is also true when isolating 2021: in this case, the sample exhibits an almost double coefficient for platform work.

Secondly, almost half (N=341) of platform workers identifies as unemployed. This allows for a comparison with the rest of the unemployed population, which allows to access a richer set of covariates concerning reasons for not working, for having quit one's previous job position, issues in finding a new job related to under- and over-skilling, gender and ethnic biases, and job search channels. Filtering for these covariates allows to retrieve the impact of platform work beyond individual skills, disadvantages, and characteristics, reducing the risk of omitted variables by including variables that could correlate with unobserved characteristics of individuals. In Table C.4 the *prima facie* negative association between platform work and lower levels of income is confirmed, and the link between the post-Covid year and platform work is similarly not verified. When looking at the probability to postpone necessary medical treatment, platform work plays a role, and a larger one when looking only at 2021; however, the magnitude of the coefficient is slightly lower than for employed individuals.

Thirdly, to strengthen our interpretation that platform work is, in itself, a source of negative variation in household income, we substitute the dummy for platform work with an item drawn from a follow-up question in the PLUS. The question is built asking the platform worker whether the income derived from platform work is useful to meet accessory expenses, important in the budget, or essential for economic survival. The latter two categories are grouped to generate a categorical variable equal to 0 for no platform work, 1 for non-essential platform work, and 2 for essential platform work. Equation 3.1 is estimated substituting the dummy for platform work with this three-tiered item. This is to ascertain that we are not capturing an effect related to people working on platforms only marginally. The results of the regressions (Table C.6) on essential platform work show that, while essential platform work has larger correlation coefficients with respect to lower household income brackets, also non-essential platform work is strongly correlated with a lower income. Economic insecurity, on the other hand, greatly increases for those platform workers reporting to find platform work necessary. As the second regression in Table C.7 shows, this can largely be explained by the after-Covid role of essential platform work.

3.5 Discussion and conclusion

In light of the evidence stemming from the PLUS dataset, platform work appears to be correlated with lower household incomes and with higher economic insecurity. Thus, the economic conditions of platform workers appear to be significantly worse than their non-platform counterparts, confirming the findings by multiple scholars that describe how platform work is performed by workers earning low pay and experiencing high job volatility (Cirillo et al., 2023a; Aloisi and De Stefano, 2022; Urzì Brancati et al., 2019; Berg et al., 2018). The number of platform workers increased significantly after the Covid-19 crisis (Bergamante et al., 2022), and platform work could have partially acted as a buffer against the most brutal economic consequences of the crisis. The vulnerability of platform workers, marked by the increased likelihood of not being able to meet medical expenses, must be highlighted.

This chapter aims to explain part of the influence that platform work has on economic conditions through changes in tasks associated with platform work. It has been shown how tasks that lead to worsened outcomes in terms of income have become relatively more relevant as the platform economy matured. Delivery work has become a source of insecurity and low pay possibly because of a switch between an (old) class of workers performing the job on the side and (a new) one depending on it for its essential needs (Bonifacio, 2023; Gregory, 2021). Micro-working, always connected with low pay rates, has grown in connection with Covid (and with the development of AI, Tubaro and Casilli (2020)). Cleaning work, while being less platformised than other types of work, is consistently less paid than alternatives, potentially reflecting existing gender biases in the labour market (Bonifacio and Pais, 2025). Platform-mediated labour, left unbridled, is mostly linked with lower-paying jobs: those jobs that were at the high end of platform work (freelancing, driving) have become less and less relevant while platform work has become a tool for intermediating precarious and low pay occupation. The economic conditions of platform workers in these occupations could improve as an outcome of regulation, since the approval and enforcement of the Platform Work Directive, yet the structural transformation of what 'platform work' means should be acknowledged.

Decreases and inequalities in the number of hours worked also provide strong explanations to the phenomenon of decreasing incomes and higher insecurity related to platform work. Platform workers are allocated on average shorter workdays. Platform labour markets may suffer from over-participation, with workers exceeding labour demand: the reason may lie in the model of "free-to-work" adopted by most platforms, in which the barriers to entry, to access a job, are minimal. Another consequence of this lack of barriers and regulations is that a minority of workers is able to work much longer hours: platforms thus contribute to inequality in hours worked among workers. Apparently, however, this comes to no benefit to platform workers in overtime, as Table 3.5 shows. On the contrary, the overtime in platform work could highlight the partial unpaid idleness platform workers face, with waiting times between one task and another.

Robustness checks substantially confirm the general picture. Even when controlling for multiple measures of economic distress and worker features, as in the regression pertaining to the employed or unemployed population, platform work appears to maintain its distinct characteristics. The use of Coarsened Exact Matching also substantially strengthens the validity of the results. Observations are matched to their closest neighbour in terms of a wide range of characteristics, partially ruling out self-selection concerns that certain types of workers could cater to platform work relatively more, biasing the results.

This work presents some limitations. The most important limitation has to do with the use of household income in place of individual measures of earnings: even controlling for a number of factors such as number of household members and number of children, household income is only an approximation of individual income, particularly as this income cannot be readily traced back to platform work. A second kind of limitation deals with the interpretation of platform work by the workers: some of them do not consider themselves employed, and some platforms blur the boundaries between different platform tasks. Third, migrant work tends to be under-reported in most accounts of platform work – leading to bias in reports of education and income (Van Doorn and Vijay, 2024; Zwysen and Piasna, 2024). Fourth, the lack of a panel component in the surveys does not allow a robust estimation of the impacts of platform work across time, or the estimation of stronger econometric models with a causal interpretation.

The present work provides support for an hours cap as a necessary corollary to any regulation of platform work, in order to grant fairer outcomes to those workers involved in the platform economy and avoid further polarisation between workers. A minimum of guaranteed working hours should follow the access of a new worker to the platform. Further, the article provides support for legislation mandating payment for idle time. Similarly, this chapter supports the view that commission caps and task-based increases across the board can improve the wellbeing of platform workers, as in Fisher (2024b,a).

Appendix for Chapter III

Tables

Table C.1: Descriptive statistics - Main sample

	2018		2021		
	No platform	Platform work	No platform	Platform work	Total
Observations	44,778 (49.1%)	222 (0.2%)	45,735 (50.1%)	484 (0.5%)	91,219 (100.0%)
household members	2.984 (1.200)	3.216 (1.247)	2.884 (1.135)	2.707 (1.345)	2.933 (1.170)
Number of children	1.130 (1.106)	0.532 (1.001)	0.682 (0.950)	0.779 (0.865)	0.902 (1.053)
Number of breadwinners	1.779 (0.810)	1.662 (0.861)	1.719 (0.670)	1.627 (0.773)	1.749 (0.745)
household income brackets					
$<$1000€	3,423 (9.3%)	35 (17.9%)	3,141 (7.6%)	55 (11.6%)	6,654 (8.4%)
1001-1500€	7,096 (19.2%)	48 (24.5%)	7,058 (17.1%)	104 (22.0%)	14,306 (18.1%)
1501-2000€	7,877 (21.3%)	36 (18.4%)	8,842 (21.4%)	149 (31.5%)	16,904 (21.4%)
2001-3000€	10,028 (27.2%)	44 (22.4%)	11,730 (28.4%)	113 (23.9%)	21,915 (27.8%)
3001-5000€	6,676 (18.1%)	22 (11.2%)	8,549 (20.7%)	42 (8.9%)	15,289 (19.4%)
$>$5000€	1,833 (5.0%)	11 (5.6%)	1,963 (4.8%)	10 (2.1%)	3,817 (4.8%)
Postponing necessary medical treatment	9,070 (20.3%)	82 (36.9%)	9,383 (20.5%)	305 (63.0%)	18,840 (20.7%)
Education					
Elementary school	1,243 (2.8%)	2 (0.9%)	423 (0.9%)	4 (0.8%)	1,672 (1.8%)
Middle school	8,242 (18.4%)	36 (16.2%)	5,130 (11.2%)	38 (7.9%)	13,446 (14.7%)
High school	21,866 (48.8%)	117 (52.7%)	26,287 (57.5%)	276 (57.0%)	48,546 (53.2%)
College degree	13,427 (30.0%)	67 (30.2%)	13,895 (30.4%)	166 (34.3%)	27,555 (30.2%)
Not born in Italy	1,194 (2.7%)	9 (4.1%)	1,036 (2.3%)	11 (2.3%)	2,250 (2.5%)
Area of Italy					
North-West	12,122 (27.1%)	49 (22.1%)	11,503 (25.2%)	106 (21.9%)	23,780 (26.1%)
North-East	8,787 (19.6%)	34 (15.3%)	8,920 (19.5%)	97 (20.0%)	17,838 (19.6%)
Centre	9,220 (20.6%)	49 (22.1%)	8,548 (18.7%)	60 (12.4%)	17,877 (19.6%)
South and Islands	14,649 (32.7%)	90 (40.5%)	16,764 (36.7%)	221 (45.7%)	31,724 (34.8%)
Living in a 250k+ city	6,505 (14.5%)	50 (22.5%)	7,156 (15.6%)	99 (20.5%)	13,810 (15.1%)
Employment condition					
Employed	19,945 (44.5%)	76 (34.2%)	18,696 (40.9%)	289 (59.7%)	39,006 (42.8%)
Unemployed and looking	6,236 (13.9%)	74 (33.3%)	8,365 (18.3%)	118 (24.4%)	14,793 (16.2%)
Retired	9,925 (22.2%)	5 (2.3%)	6,024 (13.2%)	3 (0.6%)	15,957 (17.5%)
Unemployed and not looking	5,250 (11.7%)	21 (9.5%)	6,729 (14.7%)	32 (6.6%)	12,032 (13.2%)
Student	3,422 (7.6%)	46 (20.7%)	5,921 (12.9%)	42 (8.7%)	9,431 (10.3%)
Female	24,545 (54.8%)	102 (45.9%)	26,866 (58.7%)	151 (31.2%)	51,664 (56.6%)
Age					
18-24	3,483 (7.8%)	37 (16.7%)	10,334 (22.6%)	56 (11.6%)	13,910 (15.2%)
25-29	4,298 (9.6%)	64 (28.8%)	8,001 (17.5%)	120 (24.8%)	12,483 (13.7%)
30-39	6,681 (14.9%)	47 (21.2%)	7,791 (17.0%)	136 (28.1%)	14,655 (16.1%)
40-49	7,734 (17.3%)	41 (18.5%)	4,653 (10.2%)	94 (19.4%)	12,522 (13.7%)
50-64	14,182 (31.7%)	28 (12.6%)	9,632 (21.1%)	77 (15.9%)	23,919 (26.2%)
65-74	8,400 (18.8%)	5 (2.3%)	5,324 (11.6%)	1 (0.2%)	13,730 (15.1%)
Platform tasks					
Driving		56 (25.2%)		12 (2.5%)	68 (9.6%)
Merchandise delivery		13 (5.9%)		71 (14.7%)	84 (11.9%)
Food delivery		34 (15.3%)		176 (36.4%)	210 (29.7%)

Table C.1: Descriptive statistics - Main sample

	2018		2021		
	No platform	Platform work	No platform	Platform work	Total
Micro-working and other online		18 (8.1%)		180 (37.2%)	198 (28.0%)
Cleaning		50 (22.5%)		38 (7.9%)	88 (12.5%)
Other	0 (.%)	70 (31.5%)	0 (.%)	7 (1.4%)	77 (10.9%)

Table C.2: The relationship between platform work and household income - Employed

	(1)	(2)
	OP	OP-2021
Platform work	-0.199***	-0.187
	(0.0582)	(0.126)
PW×2021		0.0316
		(0.141)
Controls	YES	YES
Area FE	YES	YES
Year FE	YES	NO
Area×Year FE	YES	NO
Observations	33791	33791
Pseudo-R^2	0.122	0.121
Log likelihood	-47785.5	-47873.7
χ^2	13321.1	13144.7

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, residence in a 250k+ city, employment status, sex, age, workplace size (number of employees), union presence, overtime work, night-time work, holiday work, contract presence, part-time contract, type of previous contract, workplace satisfaction, product/process innovation in the workplace, firing behaviour of the firm, duration of job search.

Table C.3: The relationship between platform work and probability of postponing medical treatment for financial reasons - Employed

	(1)	(2)
	Probit	2021
Platform work	0.903***	0.440**
	(0.0732)	(0.154)
PW×2021		0.600***
		(0.175)
Controls	YES	YES
Area FE	YES	YES
Year FE	YES	NO
Area×Year FE	YES	NO
Constant	-0.580**	-0.523**
	(0.179)	(0.177)
Observations	38676	38676
Pseudo-R^2	0.0992	0.0989
Log likelihood	-15552.0	-15557.4
χ^2	3427.2	3416.5

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, residence in a 250k+ city, employment status, sex, age, workplace size (number of employees), union presence, overtime work, night-time work, holiday work, contract presence, part-time contract, type of previous contract, workplace satisfaction, product/process innovation in the workplace, firing behaviour of the firm, duration of job search.

Table C.4: The relationship between platform work and household income - Unemployed

	(1)	(2)
	OP	OP-2021
Platform work	-0.199*	-0.360**
	(0.0775)	(0.120)
PW×2021		0.276
		(0.156)
Controls	YES	YES
Area FE	YES	YES
Year FE	YES	NO
Area×Year FE	YES	NO
Observations	21467	21467
Pseudo-R^2	0.106	0.0977
Log likelihood	-30776.6	-31069.2
χ^2	7313.1	6727.9

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, residence in a 250k+ city, employment status, sex, age, reasons for not working, reasons for losing one's job, job search channels and intensity of use, different difficulties in finding work due to discrimination or inadequate vacancy specifics.

Table C.5: The relationship between platform work and probability of postponing medical treatment for financial reasons - Unemployed

	(1)	(2)
	Probit	2021
Platform work	0.622***	0.407**
	(0.0892)	(0.132)
PW×2021		0.401*
		(0.179)
Controls	YES	YES
Area FE	YES	YES
Year FE	YES	NO
Area×Year FE	YES	NO
Constant	-0.713***	-0.755***
	(0.141)	(0.138)
Observations	24987	24987
Pseudo-R^2	0.0400	0.0388
Log likelihood	-15110.7	-15130.4
χ^2	1260.8	1221.4

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, residence in a 250k+ city, employment status, sex, age, reasons for not working, reasons for losing one's job, job search channels and intensity of use, different difficulties in finding work due to discrimination or inadequate vacancy specifics.

Table C.6: Essential vs. non-essential platform work and household income

	(1)	(2)
	OP	OP-2021
Non-essential platform work	-0.264***	-0.159
	(0.0737)	(0.102)
Essential platform work	-0.401***	-0.323**
	(0.0520)	(0.119)
Non-essential PW×2021		-0.224
		(0.147)
Essential PW×2021		-0.0948
		(0.132)
Controls	YES	YES
Area FE	YES	YES
Year FE	YES	NO
Area×Year FE	YES	NO
Observations	77238	77238
Pseudo-R^2	0.125	0.124
Log-likelihood	-112172.9	-112215.7
χ^2	31953.3	31867.7

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, number of breadwinners in the household, residence in a 250k+ city, employment status, sex, age.

Table C.7: Essential vs. non-essential platform work and probability of postponing medical treatment

	(1)	(2)
	Probit	2021
Non-essential platform work	0.468***	0.439***
	(0.0897)	(0.123)
Essential platform work	1.181***	0.400**
	(0.0635)	(0.137)
Non-essential PW×2021		0.0600
		(0.179)
Essential PW×2021		1.010***
		(0.155)
Controls	YES	YES
Area FE	YES	YES
Year FE	YES	YES
Area×Year FE	YES	YES
Constant	-0.849***	-0.800***
	(0.0476)	(0.0466)
Observations	89219	89219
Pseudo-R^2	0.0762	0.0755
Log-likelihood	-41546.0	-41577.2
χ^2	6857.9	6795.6

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include: education, Italy-born, number of household members, number of children, number of breadwinners in the household, residence in a 250k+ city, employment status, sex, age.

Table C.8: Descriptive statistics - Employed

	2018		2021		
	No platform	Platform work	No platform	Platform work	Total
Observations	19,945 (51.1%)	76 (0.2%)	18,696 (47.9%)	289 (0.7%)	39,006 (100.0%)
Log hours worked	3.348 (0.899)	3.349 (0.917)	3.523 (0.461)	2.462 (1.176)	3.425 (0.736)
Number of family members	3.083 (1.196)	2.934 (1.289)	2.831 (1.160)	2.626 (1.335)	2.959 (1.187)
Number of children	1.094 (1.091)	0.421 (0.868)	0.650 (0.919)	0.986 (0.897)	0.879 (1.034)
Number of breadwinners	1.988 (0.776)	2.013 (0.841)	1.897 (0.664)	1.723 (0.740)	1.942 (0.726)

Table C.8: Descriptive statistics - Employed

	2018		2021		
	No platform	Platform work	No platform	Platform work	Total
Level of satisfaction (4-tier Rikert scale)	2.938 (0.752)	2.645 (0.795)	2.728 (0.734)	2.734 (0.647)	2.836 (0.750)
Household income brackets					
Less than 1000€	714 (4.3%)	9 (12.7%)	752 (4.4%)	21 (7.3%)	1,496 (4.4%)
1001-1500€	2,236 (13.4%)	11 (15.5%)	2,394 (14.1%)	57 (19.9%)	4,698 (13.8%)
1501-2000€	3,175 (19.1%)	13 (18.3%)	3,197 (18.8%)	90 (31.4%)	6,475 (19.0%)
2001-3000€	5,407 (32.5%)	23 (32.4%)	5,238 (30.8%)	84 (29.3%)	10,752 (31.6%)
3001-5000€	3,992 (24.0%)	11 (15.5%)	4,373 (25.7%)	26 (9.1%)	8,402 (24.7%)
Over 5000€	1,132 (6.8%)	4 (5.6%)	1,063 (6.2%)	9 (3.1%)	2,208 (6.5%)
Education					
Primary school	72 (0.4%)	1 (1.3%)	14 (0.1%)	1 (0.3%)	88 (0.2%)
Middle school	2,283 (11.4%)	5 (6.6%)	977 (5.2%)	10 (3.5%)	3,275 (8.4%)
High school	9,449 (47.4%)	36 (47.4%)	9,500 (50.8%)	156 (54.0%)	19,141 (49.1%)
College	8,141 (40.8%)	34 (44.7%)	8,205 (43.9%)	122 (42.2%)	16,502 (42.3%)
Not born in Italy	569 (2.9%)	5 (6.6%)	485 (2.6%)	6 (2.1%)	1,065 (2.7%)
Area of Italy					
North-West	5,923 (29.7%)	15 (19.7%)	5,634 (30.1%)	62 (21.5%)	11,634 (29.8%)
North-East	4,294 (21.5%)	14 (18.4%)	4,519 (24.2%)	58 (20.1%)	8,885 (22.8%)
Centre	4,382 (22.0%)	17 (22.4%)	3,674 (19.7%)	34 (11.8%)	8,107 (20.8%)
South and Islands	5,346 (26.8%)	30 (39.5%)	4,869 (26.0%)	135 (46.7%)	10,380 (26.6%)
Living in a 250k+ city	3,068 (15.4%)	20 (26.3%)	3,065 (16.4%)	56 (19.4%)	6,209 (15.9%)
Female	10,173 (51.0%)	31 (40.8%)	9,524 (50.9%)	81 (28.0%)	19,809 (50.8%)
Age in brackets					
18-24	603 (3.0%)	3 (3.9%)	2,610 (14.0%)	15 (5.2%)	3,231 (8.3%)
25-29	2,301 (11.5%)	29 (38.2%)	4,344 (23.2%)	50 (17.3%)	6,724 (17.2%)
30-39	4,237 (21.2%)	17 (22.4%)	3,841 (20.5%)	88 (30.4%)	8,183 (21.0%)
40-49	4,316 (21.6%)	18 (23.7%)	2,309 (12.4%)	72 (24.9%)	6,715 (17.2%)
50-64	7,869 (39.5%)	9 (11.8%)	5,199 (27.8%)	63 (21.8%)	13,140 (33.7%)
65-74	619 (3.1%)	0 (0.0%)	393 (2.1%)	1 (0.3%)	1,013 (2.6%)
Industry					
Agriculture	650 (3.3%)	2 (2.6%)	425 (2.3%)	9 (3.1%)	1,086 (2.8%)
Mining	78 (0.4%)	0 (0.0%)	36 (0.2%)	1 (0.3%)	115 (0.3%)
Manufacturing	2,177 (10.9%)	8 (10.5%)	1,651 (8.8%)	19 (6.6%)	3,855 (9.9%)
Energy utility	265 (1.3%)	2 (2.6%)	284 (1.5%)	17 (5.9%)	568 (1.5%)
Water utility	59 (0.3%)	0 (0.0%)	94 (0.5%)	17 (5.9%)	170 (0.4%)
Constructions	707 (3.5%)	0 (0.0%)	791 (4.2%)	26 (9.0%)	1,524 (3.9%)
Retail	1,926 (9.7%)	6 (7.9%)	1,699 (9.1%)	33 (11.4%)	3,664 (9.4%)
Logistics	549 (2.8%)	2 (2.6%)	736 (3.9%)	16 (5.5%)	1,303 (3.3%)
Ho-Re-Ca	572 (2.9%)	3 (3.9%)	855 (4.6%)	19 (6.6%)	1,449 (3.7%)
Information and communication	904 (4.5%)	6 (7.9%)	1,176 (6.3%)	16 (5.5%)	2,102 (5.4%)
Finance and insurance	884 (4.4%)	3 (3.9%)	958 (5.1%)	37 (12.8%)	1,882 (4.8%)
Real estate	114 (0.6%)	2 (2.6%)	239 (1.3%)	3 (1.0%)	358 (0.9%)
Liberal professions	1,807 (9.1%)	6 (7.9%)	1,689 (9.0%)	7 (2.4%)	3,509 (9.0%)
Administration	813 (4.1%)	4 (5.3%)	165 (0.9%)	3 (1.0%)	985 (2.5%)
Public administration, defense	1,434 (7.2%)	4 (5.3%)	1,375 (7.4%)	5 (1.7%)	2,818 (7.2%)
Education	2,948 (14.8%)	6 (7.9%)	1,993 (10.7%)	15 (5.2%)	4,962 (12.7%)
Healthcare	2,354 (11.8%)	6 (7.9%)	1,511 (8.1%)	9 (3.1%)	3,880 (9.9%)
Arts and entertainment	311 (1.6%)	2 (2.6%)	365 (2.0%)	6 (2.1%)	684 (1.8%)
Other services	1,241 (6.2%)	12 (15.8%)	1,782 (9.5%)	22 (7.6%)	3,057 (7.8%)
Housekeeping services	105 (0.5%)	2 (2.6%)	50 (0.3%)	0 (0.0%)	157 (0.4%)
International organisations	47 (0.2%)	0 (0.0%)	68 (0.4%)	3 (1.0%)	118 (0.3%)
No answer	0 (0.0%)	0 (0.0%)	754 (4.0%)	6 (2.1%)	760 (1.9%)
Part-time contract	3,248 (16.3%)	17 (22.4%)	2,777 (14.9%)	141 (48.8%)	6,183 (15.9%)
Involuntary part-time	1,549 (7.8%)	10 (13.2%)	1,623 (8.7%)	22 (7.6%)	3,204 (8.2%)
Para-subordinate	784 (3.9%)	11 (14.5%)	1,568 (8.4%)	15 (5.2%)	2,378 (6.1%)
Single-commitment self-employed	1,620 (8.1%)	12 (15.8%)	1,532 (8.2%)	33 (11.4%)	3,197 (8.2%)
The firm has let workers go recently	3,195 (16.0%)	16 (21.1%)	2,913 (15.6%)	63 (21.8%)	6,187 (15.9%)
The firm has hired workers recently	6,847 (34.3%)	32 (42.1%)	5,412 (28.9%)	67 (23.2%)	12,358 (31.7%)
The firm has used redundancy funds	645 (3.2%)	1 (1.3%)	969 (5.2%)	50 (17.3%)	1,665 (4.3%)

Table C.8: Descriptive statistics - Employed

	2018		2021		
	No platform	Platform work	No platform	Platform work	Total
The firm has used solidarity agreements	647 (3.2%)	4 (5.3%)	2,321 (12.4%)	45 (15.6%)	3,017 (7.7%)
Performance of second job	865 (4.3%)	12 (15.8%)	1,048 (5.6%)	169 (58.5%)	2,094 (5.4%)
Leaves of absence possible	1,703 (8.5%)	14 (18.4%)	3,187 (17.0%)	51 (17.6%)	4,955 (12.7%)
Overtime	2,332 (11.7%)	11 (14.5%)	2,731 (14.6%)	88 (30.4%)	5,162 (13.2%)
Night work	2,782 (13.9%)	14 (18.4%)	3,001 (16.1%)	174 (60.2%)	5,971 (15.3%)
Holiday work	7,146 (35.8%)	36 (47.4%)	5,866 (31.4%)	197 (68.2%)	13,245 (34.0%)
Risky	4,476 (22.4%)	22 (28.9%)	2,614 (14.0%)	166 (57.4%)	7,278 (18.7%)
Type of contract					
Open-ended	13,160 (66.0%)	29 (38.2%)	11,184 (59.8%)	122 (42.2%)	24,495 (62.8%)
Fixed-term	1,304 (6.5%)	7 (9.2%)	1,935 (10.3%)	32 (11.1%)	3,278 (8.4%)
Training	22 (0.1%)	0 (0.0%)	91 (0.5%)	4 (1.4%)	117 (0.3%)
Apprenticeship	305 (1.5%)	5 (6.6%)	710 (3.8%)	17 (5.9%)	1,037 (2.7%)
Insertion	0 (0.0%)	0 (0.0%)	341 (1.8%)	5 (1.7%)	346 (0.9%)
Temp	245 (1.2%)	3 (3.9%)	407 (2.2%)	18 (6.2%)	673 (1.7%)
Job sharing	0 (0.0%)	0 (0.0%)	62 (0.3%)	5 (1.7%)	67 (0.2%)
On-call	192 (1.0%)	1 (1.3%)	215 (1.1%)	11 (3.8%)	419 (1.1%)
Collaboration	506 (2.5%)	8 (10.5%)	627 (3.4%)	9 (3.1%)	1,150 (2.9%)
Occasional	103 (0.5%)	3 (3.9%)	229 (1.2%)	4 (1.4%)	339 (0.9%)
Entrepreneur	1,116 (5.6%)	4 (5.3%)	712 (3.8%)	12 (4.2%)	1,844 (4.7%)
Associate	0 (0.0%)	0 (0.0%)	48 (0.3%)	3 (1.0%)	51 (0.1%)
Individual work	2,505 (12.6%)	11 (14.5%)	1,460 (7.8%)	12 (4.2%)	3,988 (10.2%)
Family helper	104 (0.5%)	1 (1.3%)	41 (0.2%)	0 (0.0%)	146 (0.4%)
School-work	1 (0.0%)	0 (0.0%)	66 (0.4%)	1 (0.3%)	68 (0.2%)
Stage	38 (0.2%)	0 (0.0%)	58 (0.3%)	1 (0.3%)	97 (0.2%)
Professional practice	30 (0.2%)	1 (1.3%)	109 (0.6%)	2 (0.7%)	142 (0.4%)
Traineeship	56 (0.3%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	56 (0.1%)
Other employed	160 (0.8%)	2 (2.6%)	237 (1.3%)	22 (7.6%)	421 (1.1%)
Other autonomous	98 (0.5%)	1 (1.3%)	164 (0.9%)	9 (3.1%)	272 (0.7%)
Innovation in firm					
No innovation	13,560 (68.0%)	49 (64.5%)	14,953 (80.0%)	80 (27.7%)	28,642 (73.4%)
Process innovation	2,734 (13.7%)	10 (13.2%)	1,497 (8.0%)	75 (26.0%)	4,316 (11.1%)
Product innovation	812 (4.1%)	4 (5.3%)	688 (3.7%)	106 (36.7%)	1,610 (4.1%)
Process and product innovation	2,839 (14.2%)	13 (17.1%)	1,558 (8.3%)	28 (9.7%)	4,438 (11.4%)

Table C.9: Descriptive statistics - Unemployed and inactive

	2018		2021		
	No platform	Platform work	No platform	Platform work	Total
Observations	11,486 (42.8%)	95 (0.4%)	15,094 (56.3%)	150 (0.6%)	26,825 (100.0%)
Household members	3.200 (1.196)	3.295 (1.287)	2.990 (1.122)	2.780 (1.335)	3.080 (1.161)
Number of children	1.166 (1.170)	0.832 (1.217)	0.679 (0.960)	0.553 (0.764)	0.887 (1.082)
Number of breadwinners	1.311 (0.767)	1.305 (0.787)	1.384 (0.588)	1.374 (0.694)	1.350 (0.678)
household income brackets					
<1000€	2,029 (22.0%)	23 (28.4%)	2,017 (14.9%)	27 (19.1%)	4,096 (17.8%)
1001-1500€	2,879 (31.2%)	27 (33.3%)	3,343 (24.7%)	38 (27.0%)	6,287 (27.3%)
1501-2000€	2,211 (23.9%)	17 (21.0%)	3,658 (27.0%)	47 (33.3%)	5,933 (25.8%)
2001-3000€	1,395 (15.1%)	9 (11.1%)	2,943 (21.8%)	20 (14.2%)	4,367 (19.0%)
3001-5000€	558 (6.0%)	2 (2.5%)	1,296 (9.6%)	9 (6.4%)	1,865 (8.1%)
>5000€	169 (1.8%)	3 (3.7%)	272 (2.0%)	0 (0.0%)	444 (1.9%)
Education					
Elementary school	393 (3.4%)	1 (1.1%)	171 (1.1%)	3 (2.0%)	568 (2.1%)
Middle school	3,066 (26.7%)	22 (23.2%)	2,219 (14.7%)	27 (18.0%)	5,334 (19.9%)
High school	5,702 (49.6%)	53 (55.8%)	9,464 (62.7%)	95 (63.3%)	15,314 (57.1%)
College	2,325 (20.2%)	19 (20.0%)	3,240 (21.5%)	25 (16.7%)	5,609 (20.9%)
Not born in Italy	451 (3.9%)	4 (4.2%)	382 (2.5%)	5 (3.3%)	842 (3.1%)
Area of Italy					
North-West	2,193 (19.1%)	21 (22.1%)	2,604 (17.3%)	30 (20.0%)	4,848 (18.1%)

Table C.9: Descriptive statistics - Unemployed and inactive

	2018		2021		
	No platform	Platform work	No platform	Platform work	Total
North-East	1,613 (14.0%)	9 (9.5%)	2,050 (13.6%)	33 (22.0%)	3,705 (13.8%)
Centre	2,177 (19.0%)	16 (16.8%)	2,484 (16.5%)	20 (13.3%)	4,697 (17.5%)
South and Islands	5,503 (47.9%)	49 (51.6%)	7,956 (52.7%)	67 (44.7%)	13,575 (50.6%)
Living in a 250k+ city	1,577 (13.7%)	18 (18.9%)	2,248 (14.9%)	33 (22.0%)	3,876 (14.4%)
Employment condition					
Unemployed and looking	6,236 (54.3%)	74 (77.9%)	8,365 (55.4%)	118 (78.7%)	14,793 (55.1%)
Unemployed and not looking	5,250 (45.7%)	21 (22.1%)	6,729 (44.6%)	32 (21.3%)	12,032 (44.9%)
Female	8,109 (70.6%)	47 (49.5%)	10,622 (70.4%)	52 (34.7%)	18,830 (70.2%)
Age					
18-24	551 (4.8%)	5 (5.3%)	3,049 (20.2%)	23 (15.3%)	3,628 (13.5%)
25-29	1,076 (9.4%)	20 (21.1%)	2,634 (17.5%)	57 (38.0%)	3,787 (14.1%)
30-39	2,272 (19.8%)	28 (29.5%)	3,727 (24.7%)	37 (24.7%)	6,064 (22.6%)
40-49	3,418 (29.8%)	23 (24.2%)	2,344 (15.5%)	22 (14.7%)	5,807 (21.6%)
50-64	3,381 (29.4%)	17 (17.9%)	2,641 (17.5%)	11 (7.3%)	6,050 (22.6%)
65-74	788 (6.9%)	2 (2.1%)	699 (4.6%)	0 (0.0%)	1,489 (5.6%)
Reasons for not working					
No work opportunities (discouraged)	612 (5.3%)	7 (7.4%)	2,435 (16.1%)	14 (9.3%)	3,068 (11.4%)
Family care	179 (1.6%)	1 (1.1%)	520 (3.4%)	3 (2.0%)	703 (2.6%)
Childcare	787 (6.9%)	0 (0.0%)	1,206 (8.0%)	1 (0.7%)	1,994 (7.4%)
No necessity - break period	34 (0.3%)	0 (0.0%)	358 (2.4%)	3 (2.0%)	395 (1.5%)
Health reasons	122 (1.1%)	0 (0.0%)	342 (2.3%)	2 (1.3%)	466 (1.7%)
Partner did not want me to work	66 (0.6%)	0 (0.0%)	321 (2.1%)	5 (3.3%)	392 (1.5%)
Inadequate education	47 (0.4%)	0 (0.0%)	317 (2.1%)	1 (0.7%)	365 (1.4%)
Education or training	241 (2.1%)	3 (3.2%)	1,050 (7.0%)	7 (4.7%)	1,301 (4.8%)
Other	165 (1.4%)	1 (1.1%)	0 (0.0%)	0 (0.0%)	166 (0.6%)
Absence of childcare services	27 (0.2%)	0 (0.0%)	88 (0.6%)	1 (0.7%)	116 (0.4%)
Well-off, no need to work	54 (0.5%)	0 (0.0%)	221 (1.5%)	4 (2.7%)	279 (1.0%)
Family did not want me to work	80 (0.7%)	0 (0.0%)	138 (0.9%)	2 (1.3%)	220 (0.8%)
Tradition of home country	17 (0.1%)	0 (0.0%)	46 (0.3%)	1 (0.7%)	64 (0.2%)
Reason for contract termination					
More time for myself	56 (0.5%)	0 (0.0%)	109 (0.7%)	4 (2.7%)	169 (0.6%)
Childcare	1,322 (11.5%)	3 (3.2%)	1,110 (7.4%)	2 (1.3%)	2,437 (9.1%)
Study reasons	92 (0.8%)	0 (0.0%)	137 (0.9%)	8 (5.3%)	237 (0.9%)
Marriage	226 (2.0%)	0 (0.0%)	100 (0.7%)	2 (1.3%)	328 (1.2%)
Firm shut down	1,159 (10.1%)	13 (13.7%)	758 (5.0%)	6 (4.0%)	1,936 (7.2%)
Family care	200 (1.7%)	1 (1.1%)	201 (1.3%)	2 (1.3%)	404 (1.5%)
Health-related	478 (4.2%)	1 (1.1%)	281 (1.9%)	4 (2.7%)	764 (2.8%)
Fired	963 (8.4%)	11 (11.6%)	430 (2.8%)	7 (4.7%)	1,411 (5.3%)
Moved	143 (1.2%)	0 (0.0%)	158 (1.0%)	2 (1.3%)	303 (1.1%)
End of contract (not renewed)	1,780 (15.5%)	14 (14.7%)	2,023 (13.4%)	12 (8.0%)	3,829 (14.3%)
Firm relocation	74 (0.6%)	0 (0.0%)	105 (0.7%)	3 (2.0%)	182 (0.7%)
Lack of satisfaction	186 (1.6%)	5 (5.3%)	249 (1.6%)	9 (6.0%)	449 (1.7%)
Seasonal/temporary work	667 (5.8%)	10 (10.5%)	723 (4.8%)	11 (7.3%)	1,411 (5.3%)
Personal reasons	573 (5.0%)	4 (4.2%)	662 (4.4%)	8 (5.3%)	1,247 (4.6%)
Unsatisfactory working conditions	348 (3.0%)	12 (12.6%)	347 (2.3%)	8 (5.3%)	715 (2.7%)
Retirement	107 (0.9%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	107 (0.4%)
Other	315 (2.7%)	4 (4.2%)	0 (0.0%)	0 (0.0%)	319 (1.2%)
Temporary interruption	148 (1.3%)	3 (3.2%)	202 (1.3%)	4 (2.7%)	357 (1.3%)
Closed my firm	218 (1.9%)	2 (2.1%)	270 (1.8%)	14 (9.3%)	504 (1.9%)

Table C.10: The relationship between platform work and household income - Ordered probit estimates, full table

	(1)	(2)	(3)	(4)
	OP	OP	OP-CEM	OP-2021

Platform work	-0.336***	-0.341***	-0.156*	-0.227**
	(0.0402)	(0.0421)	(0.0673)	(0.0759)
PW ×2021				-0.164
				(0.0911)
Elementary school		Baseline		Baseline
Middle school		0.500***	Baseline	0.501***
		(0.0316)		(0.0316)
High school		1.021***	0.412***	1.020***
		(0.0309)	(0.117)	(0.0309)
College		1.436***	0.688***	1.434***
		(0.0315)	(0.131)	(0.0315)
Born in Italy		-0.275***	-0.455	-0.277***
		(0.0250)	(0.373)	(0.0250)
Number of family members		0.123***	0.194**	0.122***
		(0.00475)	(0.0706)	(0.00475)
Number of children		0.0490***	-0.0738	0.0490***
		(0.00521)	(0.0671)	(0.00521)
Number of breadwinners		0.624***	0.674***	0.626***
		(0.00667)	(0.0775)	(0.00667)
Over 250k city		0.0713***	-0.00542	0.0726***
		(0.0108)	(0.0891)	(0.0108)
Employed		Baseline	Baseline	Baseline
Unemployed		-0.479***	-0.209*	-0.476***
		(0.0126)	(0.106)	(0.0126)
Retired		0.0314*	0.00546	0.0337*
		(0.0154)	(0.214)	(0.0154)
Inactive		-0.0941***	-0.184	-0.0906***
		(0.0137)	(0.214)	(0.0137)
Student		0.172***	0.526***	0.175***
		(0.0169)	(0.156)	(0.0169)
Biological sex		-0.164***	-0.0981	-0.163***
		(0.00807)	(0.0650)	(0.00807)
Age: 18-24		Baseline	Baseline	Baseline
Age: 25-29		-0.258***	-0.00210	-0.258***
		(0.0158)	(0.123)	(0.0158)
Age: 30-39		-0.241***	0.151	-0.240***
		(0.0166)	(0.138)	(0.0166)

Age: 40-49		-0.183***	0.213	-0.181***
		(0.0181)	(0.159)	(0.0180)
Age: 50-64		-0.0644***	0.504**	-0.0623***
		(0.0174)	(0.167)	(0.0174)
Age: 65-74		-0.0300	0.356	-0.0292
		(0.0229)	(0.365)	(0.0229)
Area FE	NO	YES	YES	YES
Year FE	NO	YES	YES	NO
Area×Year FE	NO	YES	YES	NO
Cut 1	-1.380***	0.352***	0.0791	140.2***
	(0.00641)	(0.0385)	(0.251)	(5.415)
Cut 2	-0.629***	1.340***	1.277***	141.2***
	(0.00481)	(0.0385)	(0.309)	(5.415)
Cut 3	-0.0531***	2.093***	2.147***	141.9***
	(0.00448)	(0.0388)	(0.299)	(5.415)
Cut 4	0.697***	3.049***	3.011***	142.9***
	(0.00489)	(0.0393)	(0.301)	(5.415)
Cut 5	1.659***	4.202***	4.146***	144.1***
	(0.00761)	(0.0402)	(0.303)	(5.415)
Observations	78885	77238	4522	77238
R^2	0.000267	0.125	0.113	0.124
Log-likelihood	-131599.3	-112176.0	-6480.6	-112218.5
χ^2	70.19	31947.0	524.8	31862.0

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.11: The relationship between platform work and the probability of postponing necessary medical treatment

	(1) Probit	(2) Probit	(3) CEM	(4) 2021
Platform work	0.949***	0.928***	0.703***	0.409***
	(0.0475)	(0.0501)	(0.0864)	(0.0895)
PW ×2021				0.770***
				(0.109)
Elementary school		Baseline		Baseline
Middle school		-0.134***	Baseline	-0.134***
		(0.0376)		(0.0375)

High school		-0.330***	-0.210		-0.328***
		(0.0368)	(0.181)		(0.0366)
College		-0.574***	-0.498*		-0.569***
		(0.0378)	(0.213)		(0.0376)
Born in Italian territory		0.216***	0.382		0.217***
		(0.0298)	(0.408)		(0.0298)
Number of family members		0.0370***	-0.185		0.0380***
		(0.00598)	(0.0990)		(0.00598)
Number of children		0.0692***	0.375***		0.0682***
		(0.00667)	(0.102)		(0.00666)
Number of breadwinners		-0.177***	-0.205*		-0.181***
		(0.00840)	(0.0951)		(0.00839)
250k+ city		0.0854***	0.426***		0.0848***
		(0.0140)	(0.120)		(0.0140)
Employed		Baseline	Baseline		Baseline
Unemployed		0.362***	0.0487		0.359***
		(0.0153)	(0.132)		(0.0153)
Retired		-0.118***	-0.396		-0.120***
		(0.0212)	(0.282)		(0.0212)
Inactive		0.0943***	0.269		0.0907***
		(0.0171)	(0.200)		(0.0170)
Student		0.0107	-0.140		0.00908
		(0.0222)	(0.173)		(0.0222)
Biological sex		0.195***	0.0903		0.194***
		(0.0107)	(0.105)		(0.0107)
Age: 18-24		Baseline	Baseline		Baseline
Age: 25-29		0.159***	0.122		0.157***
		(0.0206)	(0.157)		(0.0206)
Age: 30-39		0.181***	-0.191		0.177***
		(0.0216)	(0.170)		(0.0214)
Age: 40-49		0.166***	0.188		0.160***
		(0.0233)	(0.198)		(0.0228)
Age: 50-64		0.106***	-0.309		0.101***
		(0.0229)	(0.235)		(0.0225)
Age: 65-74		-0.0591	-0.637		-0.0622*
		(0.0308)	(0.563)		(0.0305)
Area FE	NO	YES	YES		YES

Year FE	NO	YES	YES	NO
Area×Year FE	NO	YES	YES	NO
Constant	-0.828***	-0.848***	-0.376	-0.796***
	(0.00473)	(0.0476)	(0.378)	(0.0460)
Observations	91219	89219	5141	89219
R^2	0.00431	0.0758	0.161	0.0751
Log-likelihood	-46260.5	-41567.9	-2607.2	-41595.5
χ^2	400.2	6814.2	347.7	6759.0

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Conclusions

This thesis has explored the different ways in which digital platforms shape labour outcomes, both within and beyond their immediate domain. Platforms emerge as power structures that connect actors and reorganise the sectors in which they operate: this research has sought to trace, empirically, how platform power reaches into local labour markets, into the internal organisation of firms, and into the working conditions of those workers labour platforms directly intermediate. Digital platforms such as Amazon reshape the labour markets in which they are present. Online intermediaries for services such as Booking have become indispensable to firms, with consequences for their internal organisational arrangements. Where platforms intermediate work directly, platform workers have become a regular feature of the economic landscape. The Introduction set out four trends through which platforms reshape labour: the compression and polarisation of wages, the fissuring of the workplace, augmented algorithmic control, and the substitution of incumbent activities. The empirical chapters take up substitution in third-party labour markets, fissuring inside firms that deal with platforms, and compression among workers whom platforms intermediate directly. Algorithmic control and digital monitoring recur throughout as the mechanisms by which platform power is transmitted.

The first chapter, using a difference-in-differences strategy with staggered adoption and not-yet-treated controls on MEF municipality-level data, has found that new Amazon facilities exert a negative impact on wages in local labour markets, particularly urban ones, indicating a possible dynamic of competition with retail. Conversely, no positive impact on employment is found, even in those local labour markets that would benefit most from new sources of employment, such as semi-peripheral and rural ones. These areas witness, instead, an increase in low-income earners at the expense of high-income ones. Our results are consistent with the evidence that the expansion of Amazon's distribution network depresses the earnings of incumbent retail workers (Chava et al., 2024): the wage effect documented here operates even where the platform's arrival is locally presented as an opportunity for job creation, and it is distributed unevenly across space. In this sense the chapter also speaks to the literature on the uneven geography of technological change, showing that platform-driven restructuring may not raise local labour demand and may instead depress it when displacing local business. Substitution, here, operates at the scale of the local labour market: where Amazon displaces incumbent activity, it hires labour back only partially and unevenly, consistent with the monopsony power of platform-led restructuring (Coveri et al., 2022).

The second chapter, using INAPP-DPS original data and multiple econometric techniques, finds that for firms in the restaurant and hospitality industries platform adoption is associated with higher levels of non-standard employment relationships. This heightened flexibility is interpreted not as a response to ordinary market volatility but as an adjustment to platform power and the uncertainty it generates. The interpretation is qualified by dependence-reducing and dependence-amplifying mechanisms: larger firms and firms that use multiple platforms do not display the association, whereas smaller firms, firms that deal with the platform leader, and firms more locked into the platform display even higher levels of non-standard employment. The latter firms tend to be concentrated in the hospitality industry, yet evidence of the effect at play in the restaurant industry has also arisen. These findings connect the firm-level evidence to the literature on platform dependence (Cutolo and Kenney, 2021) and on platform work, and give empirical content to fissuring: the contractual fragmentation platforms produce extends beyond the platform's own workforce to the supplier and vendor firms that deal with them (Coveri et al., 2022; Garcia Calvo et al., 2023).

The third chapter, using INAPP-PLUS data and probit methods, finds that household income is, on average, lower for platform workers, and that these workers are more exposed to economic insecurity. Changes in the task composition of platform work and deficits in the number of hours worked are advanced as the main explanation, with platform workers working overtime seeing no gains in economic security or income. These results align with accounts of algorithmic management and platform dependence as sources of precariousness (Wood, 2021; Schor et al., 2020). They also speak to compression and polarisation: lower average income and greater insecurity are the marks of the former, while the absence of any overtime premium qualifies the latter, suggesting that long hours alone do not secure entry into the rewarded segment and may instead result in frustration over unpaid idle time (Bonifacio, 2023).

Taken together, the three chapters constitute a contribution along three connected dimensions. In terms of data, the thesis assembles and exploits sources that have rarely been brought to bear on these questions: the spatial and temporal roll-out of Amazon facilities matched to local labour market outcomes, firm-level data capturing platform adhesion and employment composition in the hospitality sector, and worker-level data for platform workers. In terms of empirical analysis, it shifts the question from whether platform-mediated work is precarious to how platform power is transmitted—into third-party labour markets, into the internal organisation of firms, and into the incomes and economic security of intermediated workers—and addresses each channel with a design suited to it. In terms of implications, it reframes employment outcomes that might otherwise be read as purely external, competitive dynamics as adaptive responses to platform power, isolating effects that are indirect and diffuse rather than confined to the platform's own workforce.

Two main implications follow. The first is conceptual: there is a need to broaden the scope of analysis of platform work and of the platform economy beyond the boundaries previously imposed on it. While this has already been recognised in the field (Fernandez Macias et al., 2025; Garcia Calvo et al., 2023), little empirical work has moved in this direction, and few mechanisms for the diffusion and expansion of a platform's influence in the wider economy have been outlined or verified. The evidence gathered here indicates that the reorganisation of markets by platforms may deepen precarity not only by turning work into gigs, but also by pushing gig-like employment relationships into incumbent firms in traditional industries. This thesis represents a contribution toward mapping the platform economy and assessing the breadth of its reach.

The second implication concerns policy: the present work points to the need to look beyond the protection of platform workers *stricto sensu*. Subcontractors, sellers, and directly hired workers may not be adequately protected against abuses of power by platform actors enjoying unprecedented techno-economic power (Coveri et al., 2022). Rules on the responsibility of subcontracting firms, on limits to hours worked, on the commissions charged to firms, and subject on the share of turnover mediated by platforms may need to be considered in order to protect workers and small firms alike.

Clearly, this thesis has also encountered a number of limitations. The two most original data sources to which it had access lack a panel component or unique identifiers. This has constrained the range of feasible econometric strategies, as well as the additional data sources that could be linked to them. More generally, platform markets are blurry phenomena: firms do not always understand, or report in a survey, how much they depend on a platform; workers for a platform may not regard themselves as such, and may interpret the very notion of a platform differently. The mechanisms through which platform impacts diffuse need to be investigated more thoroughly: ultimately, platform markets may be phenomena so large that they exceed traditional data sources or units of analysis.

Future research follows directly from these limitations. An extension of the Amazon study to Europe, or the use of more granular data on firms and workers, are two natural avenues; more broadly, the design used for Amazon could be applied to other platforms, provided they reached different cities at different times. As the platform economy matures, the effects of platform participation on firms will become more apparent, and a broader study of the service sector is warranted: many firms, such as supermarkets, real estate agencies, car dealers, beauty parlours and barbershops, are adopting platform-like characteristics, and the labour implications of this platformisation process warrant scrutiny. Concerning platform workers in the narrow sense, the position of immigrant and minority workers deserves particular attention: their relative preference for platform work appears to stem from a different set of skills with respect to natives, and estimating the consequences of lower labour-supply elasticities for their livelihoods and working conditions would also allow potential cases of platform monopsony in specific labour-market segments to be investigated.

This thesis has aimed to make some of the consequences of structural change represented by platforms more tractable, by documenting concrete channels through which platform power reaches workers and firms. Platforms are best understood as one iteration of a longer trajectory of technological change (Braverman, 1998; Dosi, 1982; Freeman et al., 1988), whose distributional effects are neither automatic nor uniform but depend on how the technology is organised and governed. Establishing those effects empirically is a precondition for further work and policy advocacy.

Bibliography

K. Abraham, J. Haltiwanger, K. Sandusky, and J. Spletzer. Measuring the gig economy: Current knowledge and open issues. *Measuring and Accounting for Innovation in the 21st Century*, 2017.

K. G. Abraham and S. K. Taylor. Firms' use of outside contractors: Theory and evidence. *Journal of Labor Economics*, 14(3):394–424, 1996.

D. Acemoglu and D. Autor. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, volume 4, pages 1043–1171. Elsevier, 2011.

D. Acemoglu and P. Restrepo. Robots and jobs: Evidence from us labor markets. *Journal of political economy*, 128(6):2188–2244, 2020.

Z. J. Acs, A. K. Song, L. Szerb, D. B. Audretsch, and E. Komlosi. The evolution of the global digital platform economy: 1971–2021. *Small Business Economics*, 57:1629–1659, 2021.

L. Aguiar and J. Waldfogel. Platforms, power, and promotion: Evidence from spotify playlists. *The Journal of Industrial Economics*, 69(3):653–691, 2021.

C. Alaimo and J. Kallinikos. *Data rules: Reinventing the market economy.* MIT Press, 2024.

J. Alimahomed-Wilson and E. Reese. *The cost of free shipping: Amazon in the global economy.* Pluto books, 2020.

Y. Allaire and M. E. Firsirotu. Coping with strategic uncertainty. *MIT Sloan Management Review*, 30(3):7, 1989.

A. Aloisi. Platform work in europe: Lessons learned, legal developments and challenges ahead. *European Labour Law Journal*, 13(1):4–29, 2022.

A. Aloisi and V. De Stefano. *Your Boss Is an Algorithm: Artificial Intelligence, Platform Work and Labour.* Bloomsbury Publishing, 2022.

E. J. Altman, F. Nagle, and M. L. Tushman. The translucent hand of managed ecosystems: Engaging communities for value creation and capture. *Academy of Management Annals*, 16(1):70–101, 2022.

B. Y. An and J. Chung. Who bears the brunt of disruptive innovation? the effect of grocery e-commerce on local retail competitors. *Journal of Regional Science*, 65(3):843–865, 2025.

S. J. Ashford, E. George, and R. Blatt. 2 old assumptions, new work: The opportunities and challenges of research on nonstandard employment. *Academy of management annals*, 1(1):65–117, 2007.

J. Atkinson. Manpower strategies for flexible organisations. *Personnel Management*, 16(8):28–31, 1984.

D. Autor. The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty. Technical report, National Bureau of Economic Research, 2022.

D. Autor, D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen. The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2):645–709, 2020.

S. Baiocco, E. Fernández-Macías, U. Rani, and A. Pesole. The algorithmic management of work and its implications in different contexts. Technical report, JRC Working Papers Series on Labour, Education and Technology, 2022.

P. Balsiger, T. Jammet, N. Cianferoni, and M. Surdez. Coping with digital market re-organization: How the hotel industry strategically responds to digital platform power. *Competition & Change*, 27(1):163–183, 2023.

P. Barbieri and S. Scherer. Labour market flexibilization and its consequences in italy. *European sociological review*, 25(6):677–692, 2009.

A. Batch, B. Bridgman, A. Dunn, and M. Gholizadeh. Consumption zones. *Journal of Economic Geography*, 25(2):191–213, 2025.

A. Bauer and S. Fernández Guerrico. Effects of e-commerce on local labor markets. *IZA Discussion Paper*, 2023.

D. Bearson, M. Kenney, and J. Zysman. Measuring the impacts of labor in the platform economy: new work created, old work reorganized, and value creation reconfigured. *Industrial and Corporate Change*, 30(3):536–563, 2021.

P. Belleflamme and M. Peitz. Inside the engine room of digital platforms: Reviews, ratings, and recommendations. *SSRN*, 2018.

P. Belleflamme and M. Peitz. *The Economics of Platforms*. Cambridge University Press, 2021.

C. Benvegnù, B. Haidinger, and D. Sacchetto. Restructuring labour relations and employment in the european logistics sector. *Reconstructing solidarity: labour unions, precarious work, and the politics of institutional change in Europe*, pages 83–103, 2018.

J. Berg, M. Furrer, E. Harmon, U. Rani, and M. S. Silberman. *Digital labour platforms and the future of work: Towards decent work in the online world*. ILO, 2018.

F. Bergamante, F. della Ratta-Rinaldi, M. De Minicis, and E. Mandrone. Lavoro virtuale nel mondo reale: i dati dell'indagine inapp-plus sui lavoratori delle piattaforme in italia. Technical report, Istituto Nazionale per l'Analisi delle Politiche Pubbliche, 2022.

F. Biagi and M. Falk. The impact of ict and e-commerce on employment in europe. *Journal of Policy Modeling*, 39(1):1–18, 2017.

E. Bonacich and J. B. Wilson. *Getting the goods: Ports, labor, and the logistics revolution.* Cornell University Press, 2011.

F. Bonifacio. *Fare il Rider: Pratiche, saperi e traiettorie di una professione emergente.* Mimesis, 2023.

F. Bonifacio and I. Pais. How platformisation is shaping the future of domestic work. a mapping of home care and cleaning platforms in six eu countries. *A Mapping of Home Care and Cleaning Platforms in Six EU Countries (September 03, 2025). ETUI Research Paper-Working Paper*, 2025.

K. Boudreau. Open platform strategies and innovation: Granting access vs. devolving control. *Management science*, 56(10):1849–1872, 2010.

K. J. Boudreau and A. Hagiu. Platform rules: Multi-sided platforms as regulators. *Platforms, markets and innovation*, 1(0):163–191, 2009.

H. Braverman. *Labor and monopoly capital: The degradation of work in the twentieth century.* nyu Press, 1998.

E. Brynjolfsson and M. D. Smith. Frictionless commerce? a comparison of internet and conventional retailers. *Management science*, 46(4):563–585, 2000.

E. Brynjolfsson, Y. Hu, and M. S. Rahman. Battle of the retail channels: How product selection and geography drive cross-channel competition. *Management Science*, 55(11):1755–1765, 2009.

E. Brynjolfsson, Y. J. Hu, and M. D. Smith. The longer tail: The changing shape of amazon's sales distribution curve. *Available at SSRN 1679991*, 2010.

F. Butollo, G. Gereffi, C. Yang, and M. Krzywdzinski. Digital transformation and value chains: introduction. *Global Networks*, 22(4):585–594, 2022.

B. Callaway and P. H. Sant'Anna. Difference-in-differences with multiple time periods. *Journal of econometrics*, 225(2):200–230, 2021.

L. D. Cameron. "making out" while driving: Relational and efficiency games in the gig economy. *Organization Science*, 33(1):231–252, 2022.

D. Card. Who set your wage? *American Economic Review*, 112(4):1075–1090, 2022.

D. Card and A. B. Krueger. Minimum wages and employment: A case study of the fast food industry in new jersey and pennsylvania. Technical report, National Bureau of Economic Research Cambridge, Mass., USA, 1993.

B. Cattero and M. D'Onofrio. Organizing and collective bargaining in the digitized "tertiary factories" of amazon: A comparison between germany and italy. *Working in Digital and Smart Organizations: Legal, Economic and Organizational Perspectives on the Digitalization of Labour Relations*, pages 141–164, 2018.

J. Cenamor. Complementor competitive advantage: A framework for strategic decisions. *Journal of Business Research*, 122:335–343, 2021.

C. Cennamo and M. M. Tavalaei. Technology system evolution: Inertia and momentum revisited. *Available at SSRN 3630686*, 2020.

M. Centra, V. Cirillo, C. Cozza, M. Deidda, F. della Ratta, M. De Minicis, S. Donà, D. Guarascio, V. Gualtieri, N. Lettieri, et al. Piattaforme, imprese e lavoro nel mercato della ristorazione, del turismo e dei trasporti in italia. i risultati dell'indagine inapp dps. In *PIATTAFORME, IMPRESE E LAVORO NEL MERCATO DELLA RISTORAZIONE, DEL TURISMO E DEI TRASPORTI IN ITALIA*. INAPP Istituto Nazionale per l'Analisi delle Politiche Pubbliche, 2024.

S. Chava, A. Oettl, M. Singh, and L. Zeng. Creative destruction? impact of e-commerce on the retail sector. *Management Science*, 70(4):2168–2187, 2024.

L. Chen, J. Yi, S. Li, and T. W. Tong. Platform governance design in platform ecosystems: Implications for complementors' multihoming decision. *Journal of management*, 48(3):630–656, 2022.

N. Chen and H.-T. Tsai. Steering via algorithmic recommendations. *The RAND Journal of Economics*, 2023.

X. Chen, Y. Yang, and J. Wei. How do new ventures thrive in ecosystem venturing: the impacts of alliance strategy and technology interdependence. *Journal of Management Studies*, 62(2):565–596, 2025.

C. Choe, D. Kang, and H. Lee. The impact of e-commerce on local retail employment: Examining heterogeneous impacts by employment and regional types. *Global Economic Review*, 53(2):99–115, 2024.

H. Chun, H. H. Joo, J. Kang, and Y. Lee. E-commerce and local labor markets: Is the "retail apocalypse" near? *Journal of Urban Economics*, 137:103594, 2023.

V. Cirillo, R. Evangelista, D. Guarascio, and M. Sostero. Digitalization, routineness and employment: An exploration on italian task-based data. *Research Policy*, 50(7):104079, 2021.

V. Cirillo, D. Guarascio, and Z. Parolin. Platform work and economic insecurity in italy. *Structural Change and Economic Dynamics*, 65:126–138, 2023a.

V. Cirillo, D. Guarascio, G. Perani, and J. Tramontano. Lavoro e piattaforme digitali: un'analisi del caso italiano. *Parolechiave*, 32(1):165–184, 2023b.

V. Cirillo, F. S. Massimo, M. Rinaldini, J. Staccioli, and M. E. Virgillito. Monopoly power upon the world of work: A workplace analysis in the logistics segment under automation. *Review of Political Economy*, pages 1–33, 2024a.

V. Cirillo, A. Mina, and A. Ricci. Digital technologies, labor market flows and training: Evidence from italian employer-employee data. *Technological Forecasting and Social Change*, 209:123735, 2024b.

V. Cirillo, D. Cutolo, D. Guarascio, M. Kenney, and J. Tramontano. Leveraging workforce flexibility to navigate platform-induced uncertainty: A study of the italian restaurant and hospitality sectors. Technical report, LEM Working Paper Series, 2025a.

V. Cirillo, F. S. Massimo, M. Rinaldini, and J. Staccioli. Logistics under automation and digitalisation: How technology displaces human work. In *Technology and Work in Services: Vulnerable Workers under Automation and Digitalisation*, pages 35–64. Springer, 2025b.

J. Collison. The impact of online food delivery services on restaurant sales. *Department of Economics, Stanford University*, 2020.

H. Costa, G. Nicoletti, M. Pisu, and C. von Rueden. Are online platforms killing the offline star? platform diffusion and the productivity of traditional firms. Technical report, OECD, 2021a.

H. Costa, G. Nicoletti, M. Pisu, and C. Von Rueden. Welcome to the (digital) jungle: Measuring online platform diffusion. Technical report, OECD, 2021b.

A. Coveri, C. Cozza, and D. Guarascio. Monopoly capital in the time of digital platforms: a radical approach to the amazon case. *Cambridge Journal of Economics*, 46(6):1341–1367, 2022.

C. Curchod, G. Patriotta, L. Cohen, and N. Neysen. Working for an algorithm: Power asymmetries and agency in online work settings. *Administrative Science Quarterly*, 65(3):644–676, 2020.

M. Cusumano, D. Yoffie, and A. Gawer. *The future of platforms*. MIT Sloan Management Review Cambridge, MA, USA, 2020.

M. A. Cusumano, A. Gawer, and D. B. Yoffie. *The business of platforms: Strategy in the age of digital competition, innovation, and power*, volume 320. Harper Business New York, 2019.

M. A. Cusumano, A. Gawer, and D. B. Yoffie. Can self-regulation save digital platforms? *Industrial and Corporate Change*, 30(5):1259–1285, 2021.

D. Cutolo and M. Kenney. Platform-dependent entrepreneurs: Power asymmetries, risks, and strategies in the platform economy. *Academy of management perspectives*, 35(4):584–605, 2021.

D. Cutolo, A. Hargadon, M. Kenney, et al. *Competing on platforms*. MIT Sloan Management Review, 2021.

S.-O. Daunfeldt, O. Mihaescu, H. Nilsson, and N. Rudholm. What happens when ikea comes to town? *Regional studies*, 51(2):313–323, 2017.

A. Davis-Blake and B. Uzzi. Determinants of employment externalization: A study of temporary workers and independent contractors. *Administrative science quarterly*, pages 195–223, 1993.

J. Daymond, E. Knight, M. Rumyantseva, and S. Maguire. Managing ecosystem emergence and evolution: Strategies for ecosystem architects. *Strategic Management Journal*, 44(4):O1–O27, 2023.

W. P. De Groen, Z. Kilhoffer, K. Lenaerts, and I. Mandl. Employment and working conditions of selected types of platform work. *Employment and working conditions of selected types of platform work*, pages 1–86, 2018.

B. De los Santos and S. Koulayev. Optimizing click-through in online rankings with endogenous search refinement. *Marketing Science*, 36(4):542–564, 2017.

A. Delfanti. Machinic dispossession and augmented despotism: Digital work in an amazon warehouse. *New media & society*, 23(1):39–55, 2021a.

A. Delfanti. *The warehouse. Workers and robots at Amazon.* Pluto Books, 2021b.

C. Doctorow. *Enshittification: Why everything suddenly got worse and what to do about it.* Verso Books, 2025.

P. Dolfen, L. Einav, P. J. Klenow, B. Klopack, J. D. Levin, L. Levin, and W. Best. Assessing the gains from e-commerce. *American Economic Journal: Macroeconomics*, 15(1):342–370, 2023.

S. G. Donald and K. Lang. Inference with difference-in-differences and other panel data. *The review of Economics and Statistics*, 89(2):221–233, 2007.

G. Dosi. Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. *Research policy*, 11(3):147–162, 1982.

J. H. Dyer, H. Singh, and W. S. Hesterly. The relational view revisited: A dynamic perspective on value creation and value capture. *Strategic Management Journal*, 39(12):3140–3162, 2018.

B. Eaton, S. Elaluf-Calderwood, C. Sørensen, and Y. Yoo. Distributed tuning of boundary resources: The case of apple's ios service system. *MIS Quarterly*, 39(1):217–243, 2015.

K. M. Eisenhardt and J. A. Martin. Dynamic capabilities: what are they? *Strategic Management Journal*, 21(10–11):1105–1121, 2000.

M. Engert, J. Evers, A. Hein, and H. Krcmar. The engagement of complementors and the role of platform boundary resources in e-commerce platform ecosystems. *Information Systems Frontiers*, 24(6):2007–2025, 2022.

D. S. Evans. Governing bad behavior by users of multi-sided platforms. *Berkeley Tech. LJ*, 27:1201, 2012.

D. S. Evans and R. Schmalensee. *Matchmakers: The new economics of multisided platforms.* Harvard Business Review Press, 2016.

A. Ezrachi and M. E. Stucke. Virtual competition, 2016.

D. Farrell, F. Greig, and A. Hamoudi. The evolution of the online platform economy: Evidence from five years of banking data. In *AEA Papers and Proceedings*, volume 109, pages 362–366. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, 2019.

C. Farronato and A. Fradkin. The welfare effects of peer entry in the accommodation market: The case of airbnb. Technical report, National Bureau of Economic Research, 2018.

E. Fernández-Macías, C. Urzì Brancati, S. Wright, and A. Pesole. The platformisation of work. *Evidence from the JRC Algorithmic Management and Platform Work Survey (AMPWork*, 2023.

E. Fernandez Macias, I. Gonzalez Vazquez, S. Torrejon Perez, and L. Nurski. Work in the digital era: How technology is transforming work and occupations. Technical report, Joint Research Centre, 2025.

J. Fisher. Monopsony power in the gig economy. Technical report, CESifo, 2024a.

J. Fisher. Worker welfare in the gig economy. *Working paper*, 2024b.

C. Forman, A. Ghose, and A. Goldfarb. Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management science*, 55(1):47–57, 2009.

C. Forman, A. Goldfarb, and S. Greenstein. The internet and local wages: A puzzle. *American Economic Review*, 102(1):556–575, 2012.

A. Fradkin. Digital marketplaces. In P. Macmillan, editor, *The New Palgrave Dictionary of Economics*, pages 1–14. Palgrave Macmillan UK, London, 2017.

M. Frapporti. The politics of platforms. exploring platforms' infrastructural role and power. In *Capitalism in the Platform Age: Emerging Assemblages of Labour and Welfare in Urban Spaces*, pages 81–95. Springer, 2024.

C. Freeman, C. Perez, et al. Structural crises of adjustment: business cycles. *Technical change and economic theory. Londres: Pinter*, 1988.

T. Fried and A. Goodchild. E-commerce and logistics sprawl: A spatial exploration of last-mile logistics platforms. *Journal of Transport Geography*, 112:103692, 2023.

A. Garcia Calvo, M. Kenney, and J. Zysman. Understanding work in the online platform economy: the narrow, the broad, and the systemic perspectives. *Industrial and Corporate Change*, 32(4): 795–814, 2023.

L. Gastaldi, F. P. Appio, D. Trabucchi, T. Buganza, and M. Corso. From mutualism to commensalism: Assessing the evolving relationship between complementors and digital platforms. *Information Systems Journal*, 2023. isj.12491.

L. Gastaldi, F. P. Appio, D. Trabucchi, T. Buganza, and M. Corso. From mutualism to commensalism: Assessing the evolving relationship between complementors and digital platforms. *Information Systems Journal*, 34(4):1217–1263, 2024.

A. Gawer. Bridging differing perspectives on technological platforms: Toward an integrative framework. *Research Policy*, 43(7):1239–1249, 2014.

A. Gawer. Digital platforms and ecosystems: remarks on the dominant organizational forms of the digital age. *Innovation*, 24(1):110–124, 2022.

A. Gawer, M. A. Cusumano, et al. *Platform leadership: How Intel, Microsoft, and Cisco drive industry innovation*, volume 5. HBSP, 2002.

A. Ghose and Y. Yao. Using transaction prices to re-examine price dispersion in electronic markets. *Information Systems Research*, 22(2):269–288, 2011.

A. Ghose, M. D. Smith, and R. Telang. Internet exchanges for used books: An empirical analysis of product cannibalization and welfare impact. *Information Systems Research*, 17(1):3–19, 2006.

G. A. Giuliani and R. Paraciani. Does the platform clean the cleaners?: an exploratory study on the platformization of dirty jobs in italy. *Cambio: rivista sulle trasformazioni sociali: 27, 1, 2024*, pages 65–78, 2024.

A. Goldfarb and C. Tucker. Digital economics. *Journal of economic literature*, 57(1):3–43, 2019.

M. Goldmanis, A. Hortaçsu, C. Syverson, and Ö. Emre. E-commerce and the market structure of retail industries. *The Economic Journal*, 120(545):651–682, 2010.

I. Gonzalez Vàzquez, E. Fernandez Macias, S. Wright, D. Villani, et al. Digital monitoring, algorithmic management and the platformisation of work in europe. *JRC Report*, 2025.

M. Graham, V. Lehdonvirta, A. Wood, H. Barnard, I. Hjorth, and D. Peter Simon. The risks and rewards of online gig work at the global margins. *Oxford Internet Institute*, 2017.

K. Gregory. 'my life is more valuable than this': Understanding risk among on-demand food couriers in edinburgh. *Work, Employment and Society*, 35(2):316–331, 2021.

R. W. Gregory, O. Henfridsson, E. Kaganer, and H. Kyriakou. The role of artificial intelligence and data network effects for creating user value. *Academy of management review*, 46(3):534–551, 2021.

G. Gu. Technology and disintermediation in online marketplaces. *Management Science*, 2024. mnsc.2021.02736.

D. Guarascio and S. Sacchi. Digital platform in italy. an analysis of economic and employment trends. *Policy Brief*, 8, 2018.

D. Guarascio, S. Sacchi, et al. Digitalizzazione, automazione e futuro del lavoro. Technical report, Istituto Nazionale per l'Analisi delle Politiche Pubbliche, 2017.

B. Gutelius and N. Theodore. The future of warehouse work: Technological change in the us logistics industry. Technical report, UC Berkeley Labor Center, 2019.

A. Hagiu and J. Wright. Don't let platforms commoditize your business. *Harvard Business Review*, 99(3):108–114, 2021.

J. V. Hall and A. B. Krueger. An analysis of the labor market for uber's driver-partners in the united states. *Ilr Review*, 71(3):705–732, 2018.

S. Hardaker. A critical perspective on the increasing power of digital platforms through the lens of conjunctural geographies. In *Geographies of the Platform Economy: Critical Perspectives*, pages 75–88. Springer, 2024.

S. He, B. Hollenbeck, and D. Proserpio. The market for fake reviews. *Marketing Science*, 2022. mksc.2022.1353.

T. J. Holmes. The diffusion of wal-mart and economies of density. *Econometrica*, 79(1):253–302, 2011.

R. A. Hunt, D. M. Townsend, J. J. Simpson, R. Nugent, M. Stallkamp, and E. Bozdag. Digital battlegrounds: The power dynamics and governance of contemporary platforms. *Academy of Management Annals*, 19(1):265–297, 2025.

T. Hurni, T. L. Huber, and J. Dibbern. Power dynamics in software platform ecosystems. *Information systems journal*, 32(2):310–343, 2022.

U. Huws. *Labor in the global digital economy: The cybertariat comes of age.* NYU Press, 2014.

U. Huws, N. Spencer, D. S. Syrdal, and K. Holts. Work in the european gig economy: Research results from the uk, sweden, germany, austria, the netherlands, switzerland and italy. *FEPS Working Paper*, 2017.

S. M. Iacus, G. King, and G. Porro. Causal inference without balance checking: Coarsened exact matching. *Political analysis*, 20(1):1–24, 2012.

M. Iansiti and R. Levien. Keystones and dominators: Framing operating and technology strategy in a business ecosystem. *Harvard Business School, Boston*, 3(1-82), 2004.

G. Ietto-Gillies and C. Trentini. Sectoral structure and the digital era. conceptual and empirical analysis. *Structural Change and Economic Dynamics*, 64:13–24, 2023.

M. G. Jacobides and I. Lianos. Ecosystems and competition law in theory and practice. *Industrial and Corporate Change*, 30(5):1199–1229, 2021.

M. G. Jacobides, C. Cennamo, and A. Gawer. Towards a theory of ecosystems. *Strategic management journal*, 39(8):2255–2276, 2018.

M. G. Jacobides, Cennamo, and A. Gawer. Externalities and complementarities in platforms and ecosystems: From structural solutions to endogenous failures. *Research Policy*, 53(1):104906, 2024.

M. H. Jarrahi, G. Newlands, M. K. Lee, C. T. Wolf, E. Kinder, and W. Sutherland. Algorithmic management in a work context. *Big data & society*, 8(2):20539517211020332, 2021.

S. Johnson and D. Acemoglu. *Power and progress: Our thousand-year struggle over technology and prosperity| Winners of the 2024 Nobel Prize for Economics.* Hachette UK, 2023.

A. L. Kalleberg. Nonstandard employment relations: Part-time, temporary and contract work. *Annual Review of Sociology*, 26(1):341–365, 2000.

S. Kang. Why do warehouses decentralize more in certain metropolitan areas? *Journal of Transport Geography*, 88:102330, 2020.

S. Kassem. Labour realities at amazon and covid-19: Obstacles and collective possibilities for its warehouse workers and mturk workers. *Global Political Economy*, 1(1):59–79, 2022.

M. Kenney and J. Zysman. The rise of the platform economy. *Issues in science and technology*, 32 (3):61, 2016.

M. Kenney, P. Rouvinen, and J. Zysman. Employment, work, and value creation in the era of digital platforms. In *Digital work and the platform economy*, pages 13–30. Routledge, 2019.

M. Kenney, D. Bearson, and J. Zysman. The platform economy matures: Measuring pervasiveness and exploring power. *Socio-economic review*, 19(4):1451–1483, 2021.

S. Kergroach and M. M. Bianchini. *The digital transformation of SMEs*. OECD Publishing, 2021.

L. M. Khan. Amazon's antitrust paradox. *Yale lJ*, 126:710, 2016.

T. Kude and T. L. Huber. Responding to platform owner moves: A 14-year qualitative study of four enterprise software complementors. *Information Systems Journal*, 35(1):209–246, 2025.

K. M. Kuhn and T. L. Galloway. With a little help from my competitors: Peer networking among artisan entrepreneurs. *Entrepreneurship theory and practice*, 39(3):571–600, 2015.

K. M. Kuhn and A. Maleki. Micro-entrepreneurs, dependent contractors, and instaserfs: Understanding online labor platform workforces. *Academy of management perspectives*, 31(3):183–200, 2017.

A. Kumar. *Monopsony capitalism: Power and production in the twilight of the sweatshop age*. Cambridge University Press, 2020.

T. L. Lee, M. Tapia, C. L. Aranzaes, S. R. Sapre, S. Shimek, S. Pinto, and A. R. Bustamante. The militarization of employment relations: racialized surveillance and worker control in amazon fulfillment centers. *Work and occupations*, 52(4):491–528, 2025.

Y. Liu, P. Yildirim, and Z. J. Zhang. Implications of revenue models and technology for content moderation strategies. *Marketing Science*, 41(4):831–847, 2022.

M. Luca and G. Zervas. Fake it till you make it: Reputation, competition, and yelp review fraud. *Management Science*, 62(12):3412–3427, 2016.

G. Mangum, D. Mayall, and K. Nelson. The temporary help industry: A response to the dual internal labor market. *ILR Review*, 38(4):599–611, 1985.

M. Marrone et al. Rights against the machines! food delivery, piattaforme digitali e sindacalismo informale: il caso riders union bologna. *Labour & Law Issues*, 1(5):1–28, 2019.

N. Martindale and V. Lehdonvirta. Labour market digitalization and social class: evidence of mobility and reproduction from a european survey of online platform workers. *Socio-Economic Review*, 21(4):1945–1965, 2023.

A. Martínez-Sánchez, M. Vela-Jiménez, M. Pérez-Pérez, and P. de-Luis-Carnicer. The dynamics of labour flexibility: Relationships between employment type and innovativeness. *Journal of Management Studies*, 48(4):715–736, 2011.

F. S. Massimo. *Mobilising work and demobilising labour under contemporary monopoly capitalism: a comparative study of the labour process and industrial relations in Amazon's logistics network.* PhD thesis, Institut d'études politiques de paris-Sciences Po, 2024.

S. F. Matusik and C. W. L. Hill. The utilization of contingent work, knowledge creation, and competitive advantage. *The Academy of Management Review*, 23(4):680–697, 1998.

D. P. McIntyre and A. Srinivasan. Networks, platforms, and strategy: Emerging views and next steps. *Strategic management journal*, 38(1):141–160, 2017.

O. Mihaescu, M. Korpi, and Ö. Öner. Does new shopping centre development benefit or harm the local suburban market? heterogeneous effects from shopping centre type and distance. *The annals of regional science*, 73(3):1339–1363, 2024.

S. Nambisan and R. A. Baron. On the costs of digital entrepreneurship: Role conflict, stress, and venture performance in digital platform-based ecosystems. *Journal of Business Research*, 2019. doi: 10.1016/j.jbusres.2019.06.037.

S. Nambisan and R. A. Baron. On the costs of digital entrepreneurship: Role conflict, stress, and venture performance in digital platform-based ecosystems. *Journal of Business Research*, 125: 520–532, 2021.

S. Nambisan, D. Siegel, and M. Kenney. On open innovation, platforms, and entrepreneurship. *Strategic Entrepreneurship Journal*, 12(3):354–368, 2018.

K. F. Nzembayie, N. Evers, and D. Urbano. Power dynamics in transaction platforms: Adaptive strategies of platform-dependent entrepreneurs. *Technovation*, 138:103114, 2024.

W. J. Orlikowski and S. V. Scott. What happens when evaluation goes online? exploring apparatuses of valuation in the travel sector. *Organization Science*, 25(3):868–891, 2014.

H. Ozalp, C. Cennamo, and A. Gawer. Disruption in platform-based ecosystems. *Journal of Management Studies*, 55(7):1203–1241, 2018.

C. Panico and C. Cennamo. User preferences and strategic interactions in platform ecosystems. *Strategic Management Journal*, 43(3):507–529, 2022.

L. E. Papke and J. M. Wooldridge. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of applied econometrics*, 11(6):619–632, 1996.

G. Parker and M. Van Alstyne. Innovation, openness & platform control. In *Proceedings of the 11th ACM conference on Electronic commerce*, pages 95–96, 2010.

G. Parker and M. Van Alstyne. Innovation, openness, and platform control. *Management Science*, 64(7):3015–3032, 2018.

G. G. Parker, M. W. Van Alstyne, and S. P. Choudary. *Platform revolution: How networked markets are transforming the economy and how to make them work for you.* WW Norton & Company, 2016.

A. Pesole, U. Brancati, E. Fernández-Macías, F. Biagi, and I. González Vázquez. Platform workers in europe. *Luxembourg: Publications Office of the European Union*, 2018.

C. Petre, B. E. Duffy, and E. Hund. "gaming the system": Platform paternalism and the politics of algorithmic visibility. *Social Media+ Society*, 5(4):2056305119879995, 2019.

J. Pfeffer and J. N. Baron. Taking the workers back out: Recent trends in the structuring of employment. *Research in Organizational Behavior*, 10:257–303, 1988.

A. Piasna, W. Zwysen, and J. Drahokoupil. The platform economy in europe: Results from the second etui internet and platform work survey. Technical report, Working Paper, 2022.

M. Pirone, M. Frapporti, F. Chicchi, M. Marrone, et al. Covid-19 impact on platform economy. a preliminary outlook. *Internal report*, 2020.

J.-C. Plantin and A. Punathambekar. Digital media infrastructures: Pipes, platforms, and politics. *Media, culture & society*, 41(2):163–174, 2019.

V. Pulignano, D. Grimshaw, M. Domecka, and L. Vermeerbergen. Why does unpaid labour vary among digital labour platforms? exploring socio-technical platform regimes of worker autonomy. *Human Relations*, 77(9):1243–1271, 2024.

K. S. Rahman and K. Thelen. The rise of the platform business model and the transformation of twenty-first-century capitalism. *Politics & society*, 47(2):177–204, 2019.

U. Rani and R. K. Dhir. Platform work and the covid-19 pandemic. *The Indian Journal of Labour Economics*, 63(Suppl 1):163–171, 2020.

A. J. Ravenelle, K. C. Kowalski, and E. Janko. The side hustle safety net: Precarious workers and gig work during covid-19. *Sociological Perspectives*, 64(5):898–919, 2021.

P. Resnick and H. R. Varian. Recommender systems. *Communications of the ACM*, 40(3):56–58, 1997.

J. Rietveld and J. Eggers. Demand heterogeneity in platform markets: Implications for complementors. *Organization Science*, 29(2):304–322, 2018.

J. Rietveld, J. N. Ploog, and D. B. Nieborg. Coevolution of platform dominance and governance strategies: Effects on complementor performance outcomes. *Academy of Management Discoveries*, 6(3):488–513, 2020.

J. Rietveld, R. Seamans, and K. Meggiorin. Market orchestrators: The effects of certification on platforms and their complementors. *Strategy Science*, 6(3):244–264, 2021.

C. Rikap. *Capitalism, power and innovation: Intellectual monopoly capitalism uncovered.* Routledge, 2021.

F. Rios-Avila, B. Callaway, and P. Sant'Anna. csdid: Difference-in-differences with multiple time periods in stata. In *Stata Conference*, page 47, 2021.

A. Risberg. A systematic literature review on e-commerce logistics: towards an e-commerce and omni-channel decision framework. *The International Review of Retail, Distribution and Consumer Research*, 33(1):67–91, 2023.

S. T. Roberts. *Behind the screen: The hidden digital labor of commercial content moderation.* University of Illinois at Urbana-Champaign, 2014.

J.-C. Rochet and J. Tirole. Platform competition in two-sided markets. *Journal of the european economic association*, 1(4):990–1029, 2003.

J.-P. Rodrigue. The distribution network of amazon and the footprint of freight digitalization. *Journal of Transport Geography*, 88, 2020.

J. Sadowski. When data is capital: Datafication, accumulation, and extraction. *Big data & society*, 6(1):2053951718820549, 2019.

S. Scholten and U. Scholten. Platform-based innovation management: directing external innovational efforts in platform ecosystems. *Journal of the Knowledge Economy*, 3(2):164–184, 2012.

J. B. Schor and W. Attwood-Charles. The "sharing" economy: labor, inequality, and social connection on for-profit platforms. *Sociology Compass*, 11(8):e12493, 2017.

J. B. Schor, W. Attwood-Charles, M. Cansoy, I. Ladegaard, and R. Wengronowitz. Dependence and precarity in the platform economy. *Theory and society*, 49(5):833–861, 2020.

S. V. Scott and W. J. Orlikowski. Reconfiguring relations of accountability: Materialization of social media in the travel sector. *Accounting, organizations and society*, 37(1):26–40, 2012.

C. Shapiro. Information rules: A strategic guide to the network economy. *Harvard Business Review Press*, 1999.

N. Srnicek. *Platform capitalism.* John Wiley & Sons, 2017.

D. Stark and I. Pais. Algorithmic management in the platform economy. *Sociologica*, 14(3):47–72, 2020.

D. Stark and I. Pais. Algorithmic management in the platform economy. *Sociologica*, 14(3):47–72, 2021.

D. Stark and P. Vanden Broeck. Principles of algorithmic management. *Organization Theory*, 5(2): 26317877241257213, 2024.

A. Sundararajan. *The sharing economy: the end of employment and the rise of crowd-based capitalism.* The MIT Press, Cambridge, Massachusetts, 2016.

A. Sundararajan. *The sharing economy: The end of employment and the rise of crowd-based capitalism.* MIT press, 2017.

M. Tapia, T. L. Lee, and C. L. Aranzaes. Confronting legacies of white dominance: Challenges to inclusive worker organizing through the storytelling of amazon warehouse workers. *Stato e mercato*, 44(1):67–100, 2024.

P. Tubaro and A. A. Casilli. Micro-work, artificial intelligence and the automotive industry. *Journal of Industrial and Business Economics*, 46(3):333–345, 2019.

P. Tubaro and A. A. Casilli. Portraits of micro-workers: The real people behind ai in france. In *2nd Crowdworking Symposium 2020*, 2020.

M. C. Urzì Brancati, A. Pesole, and E. Fernandez Macias. Digital labour platforms in europe: numbers, profiles, and employment status of platform workers. Technical report, Joint Research Centre, 2019.

B. Uzunca, D. Sharapov, and R. Tee. Governance rigidity, industry evolution, and value capture in platform ecosystems. *Research Policy*, 51(7):104560, 2022.

B. Uzzi and Z. I. Barsness. Contingent employment in british establishments: Organizational determinants of the use of fixed-term hires and part-time workers. *Social Forces*, 76(3):967–1007, 1998.

S. Vallas and J. B. Schor. What do platforms do? understanding the gig economy. *Annual review of sociology*, 46(1):273–294, 2020.

S. P. Vallas. Platform capitalism: what's at stake for workers? In *New Labor Forum*, volume 28, pages 48–59. Sage Publications Sage CA: Los Angeles, CA, 2019.

S. P. Vallas, H. Johnston, and Y. Mommadova. Prime suspect: mechanisms of labor control at amazon's warehouses. *Work and Occupations*, 49(4):421–456, 2022.

J. Van Dijck, D. Nieborg, and T. Poell. Reframing platform power. *Internet policy review*, 8(2): 1–18, 2019.

N. Van Doorn and D. Vijay. Gig work as migrant work: The platformization of migration infrastructure. *Environment and Planning A: Economy and Space*, 56(4):1129–1149, 2024.

A. R. Villadsen and J. N. Wulff. Are you 110 *Strategic Organization*, 19(2):312–337, 2021.

F. Von Briel, P. Davidsson, and J. Recker. Digital technologies as external enablers of new venture creation in the it hardware sector. *Entrepreneurship Theory and Practice*, 42(1):47–69, 2018.

J. Waldfogel. Amazon self-preferencing in the shadow of the digital markets act. Technical report, National Bureau of Economic Research, 2024.

R. D. Wang and C. D. Miller. Complementors' engagement in an ecosystem: A study of publishers'e-book offerings on amazon kindle. *Strategic Management Journal*, 41(1):3–26, 2020.

J. Wareham, P. B. Fox, and J. L. Cano Giner. Technology ecosystem governance. *Organization science*, 25(4):1195–1215, 2014.

D. Weil. The fissured workplace: Why work became so bad for so many and what can be done to improve it. In *The fissured workplace*. Harvard university press, 2015.

W. Wen and F. Zhu. Threat of platform-owner entry and complementor responses: Evidence from the mobile app market. *Strategic Management Journal*, 40(9):1336–1367, 2019.

J. C. Wiltshire. Walmart supercenters and monopsony power: How a large, low-wage employer impacts local labor markets. *Job market paper*, 2021.

A. J. Wood. Algorithmic management consequences for work organisation and working conditions. Technical report, JRC working papers series on labour, education and technology, 2021.

A. J. Wood and V. Lehdonvirta. Antagonism beyond employment: how the 'subordinated agency'of labour platforms generates conflict in the remote gig economy. *Socio-Economic Review*, 19(4): 1369–1396, 2021.

T. Wu. *The curse of bigness: how corporate giants came to rule the world.* Atlantic Books, 2020.

Y. Wu and F. Zhu. Competition, contracts, and creativity: Evidence from novel writing in a platform market. *Management Science*, 68(12):8613–8634, 2022.

Y. Wu, E. W. Ngai, P. Wu, and C. Wu. Fake online reviews: Literature review, synthesis, and directions for future research. *Decision Support Systems*, 132:113280, 2020.

P. Zanoni and M. Miszczyński. Post-diversity, precarious work for all: Unmaking borders to govern labour in the amazon warehouse. *Organization Studies*, 45(7):987–1008, 2024.

P. Zhao, G. Zervas, and X. Han. The impact of platform commission design on creators' pricing strategy and productivity. Technical report, Technical Report 2024. 6, 2024.

B. Zhou and T. Zou. Competing for recommendations: The strategic impact of personalized product recommendations in online marketplaces. *Marketing Science*, 42(2):360–376, 2023.

F. Zhu and Q. Liu. Competing with complementors: An empirical look at amazon. com. *Strategic management journal*, 39(10):2618–2642, 2018.

T. Zou and B. Zhou. Self-preferencing and search neutrality in online retail platforms. *Management Science*, 71(5):4087–4107, 2025.

S. Zuboff. *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power.* Hachette UK, 2019.

W. Zwysen and A. Piasna. Digital labour platforms and migrant workers: analysing migrants' working conditions and (over) representation in platform work in europe. *ETUI Research Paper-Working Paper*, 2024.

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