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(Internally) Buffering the risks of platform dependence: How adopting digital platforms shapes participants' firms' employment structures.

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Abstract:	While platform participation dramatically expands market access, it also creates new dependencies for firms and exposes them to distinctive risks stemming from platform owners' control over technological infrastructure and participation rules, such as opaque algorithmic changes that may affect demand and shifts in participation conditions. Drawing on power-dependence theory and internal labor market theory, we argue that firms using online platforms respond to these risks not only through external competitive strategies, as prior research has emphasized, but also through the reconfiguration of their internal employment structures. Using a unique dataset from the Digital Platform Survey (DPS), administered by Italy's National Institute for Public Policy Analysis (INAPP) to more than 20,000 hotels and restaurants, we show that firms using platforms rely more heavily on non-standard employment relationships (NSERs), including temporary, on-call, and collaboration contracts, than comparable firms that do not use platforms. We further demonstrate that this relationship reflects firms' responses to the risks inherent in platform participation and varies systematically with contingencies that shape exposure to these risks. Specifically, reliance on NSERs is weaker for factors that attenuate dependence on the platform, such as among larger firms and multihoming strategies, and stronger when dependence is amplified, such as among firms operating on dominant platforms or making platform-specific investments. Our study extends information systems research on how complementors respond to risks generated by platform governance by identifying employment reconfiguration as an internal organizational response. In doing so, we also broaden debates on platforms and labor by uncovering an indirect mechanism through which platform power contributes to workforce precarity

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1. Introduction

Contemporary businesses increasingly operate in competitive landscapes mediated by online digital platforms that broaden customer access, facilitate market interactions by mitigating frictions associated with entry and expansion, while reducing search costs and information asymmetries between producers and consumers (Jacobides, Cennamo, & Gawer, 2024; Nambisan, 2017; Kenney et al. 2021; Parker, Van Alstyne, & Choudary, 2016). Yet, there has been growing recognition that the very platforms hailed as engines of business opportunities also pose unique risks for firms that use them to secure customers. By exercising unilateral control over the technological infrastructure that mediates access to customers, as well as the governance mechanisms that regulate participation, these platforms wield an asymmetrical form of power that creates new dependencies for firms, generating uncertainty and significantly shaping their opportunities and operations (Cutolo & Kenney, 2021; Huber, Kude, & Dibbern, 2017; Hurni, Huber, & Dibbern, 2022).

In response to these emerging dynamics, recent scholarship has begun to explore how firms seek to "adapt to the new environment of platforms and undercut their dependence on them" (Balsiger, Jammet, Cianferoni, & Surdez, 2023, p. 167). This body of work has largely emphasized *external* coping strategies aimed at rebalancing these power asymmetries, such as forging alliances with other firms experiencing similar conditions (Kuhn & Galloway, 2015), diversifying across multiple platforms (Kude & Huber, 2025), creating alternative income streams outside the platform (Gastaldi, Appio, Trabucchi, Buganza, & Corso, 2023), or even invoking government intervention, as in the recent class-action lawsuit from more than 10,000 hotels against Booking.

However, these studies offer limited insight into the *internal* organizational adjustments firms may make to address the adverse effects of these power imbalances. Workforce structure is widely recognized as a lever through which firms manage environmental uncertainty (Davis-Blake & Uzzi, 1993; Ashford, George, & Blatt, 2007), yet despite increasing scholarly interest in the relationship between platforms and labor dynamics (Liu, Pei, & Zhang, 2024; Guo, Cheng, & Pavlou, 2025; Vallas & Schor, 2020), we still lack systematic evidence on whether and how firms also reconfigure their employment arrangements as an adaptive response to the specific risks arising from platform participation. This omission is consequential: if platform adoption reshapes how firms organize work, then, as platforms become a dominant way of organizing economic activity, they become a structural driver of labor precarity that also affects workers who have no direct relationship with the platform itself. We therefore ask the following research question: *How do platforms affect participant firms' internal employment structures?*

Previous research provides evidence that, with asymmetrical control over governance mechanisms, platform owners can actively generate substantial risks for participating firms, including uncertainty arising from opaque algorithmic systems and unilateral modifications to fee structures or participation rules that reshape firms' conditions of access and visibility (Cutolo & Kenney, 2021; Huber et al. 2017; Curchod, Patriotta, Cohen, & Neysen, 2020). Borrowing arguments from power-dependence theory (Emerson, 1962) and the internal labor market (ILM) theory (Doeringer & Piore, 1971; Baron, 1984; Baron, Dobbin, & Jennings 1986) we propose that firms respond to these risks not only through the external market strategies documented in the literature, but also by increasing their reliance on non-standard employment relationships (NSERs) as a buffering mechanisms. However, because these platform-induced risks are not experienced uniformly across firms that rely on platforms, we further contend that reliance on NSERs decreases with factors that attenuate exposure to these risks, such as firm size and multihoming (i.e., diversifying across platforms), and increases with factors that amplify it, such as engagement with a dominant platform and platform-specific investments.

We test these arguments using a unique dataset from the Digital Platform Survey (DPS), administered by the Italian National Institute for Public Policy Analysis (INAPP), covering 20,638 Italian firms in the restaurant (13,739) and hotel (6,899) industries. Our analysis indicates that, ceteris paribus, firms using platforms to reach their customers are more likely than comparable firms not using platforms to have a higher share of NSERs. We corroborate this association by applying Coarsened Exact Matching, replicating the analysis in the pre-COVID period, controlling for stable employment shares, and using difference-in-differences fixed-effects analysis leveraging firms that adopted platforms during the 2020 pandemic shock. Consistent with our theoretical predictions, we also show that, among firms using platforms, the effect is more pronounced for structural characteristics or competitive choices attenuating or amplifying a firm's level of platform dependence.

Our study makes three important contributions. First, we extend research on how complementors try to cushion the adverse effects of platform owner moves and governance decisions by theorizing and empirically documenting that employment configuration serves as an internal organizational response to the risks inherent in platform participation (Kude & Huber, 2025; Liu et al., 2025; Huber et al., 2017; Xia, Chen, & Fang, 2025). Second, we refine our understanding of power dynamics in platform ecosystems (Hurni et al., 2022; Hunt et al., 2025; Cutolo & Kenney, 2021) by showing that its consequences for complementors are systematically heterogeneous, indicating that platform dependence is not binary but continuous and multidimensional, with distinct organizational implications. Third, our findings contribute to the discussion on digital platforms and labor (Cirillo, Guarascio, & Parolin, 2023; Liu, Pei, & Zhang, 2024; Garcia Calvo, Kenney, & Zysman, 2023; Guo et al., 2025; Vallas & Schor, 2020). We demonstrate that platforms' influence extends beyond the direct mediation of work practices and the introduction of ambiguous and precarious employment statuses, such as is the case of gig workers (Kuhn & Maleki, 2017; Sundararajan, 2016), to spill over into the employment practices of established firms, reshaping employment relationships across industries where platforms are increasingly becoming the prominent form of organizing economic activity.

2. Theoretical background

2.1 Power and Dependence in the Platform Economy

Digital platforms have seamlessly woven themselves into the fabric of modern life, coalescing into powerful intermediaries that are reorganizing how consumers and producers interact across a growing number of industries (Evans & Schmalensee, 2016; Parker et al., 2016; Kenney, Bearson & Zysman 2021). Leveraging network effects and winner-take-all dynamics, a small number of platforms tend to dominate in each industry, concentrating the majority of consumer traffic and transactions (Jacobides, Cennamo, & Gawer, 2018). Therefore, for an ever-growing number of businesses, participation in these platform-mediated markets is less a strategic choice than a competitive necessity because firms that opt out risk losing access to a fundamental channel through which consumers discover and purchase their services (Jacobides & Lianos, 2021; Khan, 2016).

Given this extensive influence, it is no surprise that digital platforms are under intense scrutiny for the influence they exert over platform-based businesses and society writ large (Belleflamme & Peitz, 2021; Jacobides & Lianos, 2021). Power, in fact, is a central and defining feature of digital platforms (Hunt et al., 2025; Jacobides et al., 2024; Cutolo & Kenney, 2021). Unlike conventional markets, where the rules of exchange emerge from competitive interaction among participants (and government regulation), digital platforms are managed environments (Altman, Nagle, & Tushman, 2022), in which the platform owner retains unilateral control over the conditions of participation (Boudreau & Hagiu, 2009; Parker & Van Alstyne, 2018). Platforms set the rules that regulate access to and participation in the marketplace, including the fee structures that determine how value is divided between the platform and its participants (Halckenhaeusser, Foerderer, Heinzl, & Henfridsson, 2025; Liu, Yildirim, & Zhang, 2022). Algorithms govern search and shape which firms are visible to potential customers and which are not (Curchod et al., 2020; Aguiar & Waldfogel, 2021), and ultimately who is allowed to operate on the platform (Evans, 2012). In addition to these key governance levers, platforms' power is ultimately embedded and expressed in the unilateral control over the technological architecture upon which firms must build their offerings to reach customers (Ghazawneh & Henfridsson, 2013; Karhu, Gustafsson, & Lyytinen, 2018; Tiwana, Konsynski, & Bush, 2010).

Previous research has thus characterized these power imbalances inherent in the relationship between platform owners and firms that use platforms as creating a condition of platform dependence that generates risks that significantly constrain business practices (Cutolo & Kenney, 2021). Platform dependence is fundamentally endogenous, as it is not a background condition of the environment but is actively produced by the platform's choices. For instance, the possibility of technological and regulatory evolution in the platform ecosystem, driven by security or competitive reasons, may expose platform-dependent firms to sudden margin erosion or revenue declines (Liu et al., 2022; Wu & Zhu, 2022; Zhao, Zervas, & Han, 2024). Relatedly, frequent and opaque changes to the algorithms that allocate visibility have drastic impacts on firms' demand (Oestreicher-Singer & Sundararajan, 2012; Tan, Netessine, & Hitt, 2014; Zhang et al., 2026), particularly when the platform owners often use their ability to promote specific offerings to nudge customers towards their own offerings rather than potential best-value or better options (Foerderer, Lueker, & Heinzl, 2021; De Los Santos & Koulayev, 2017; Zou & Zhou, 2024). In more extreme cases, platforms can also leverage asymmetric visibility over platform information to identify and replicate successful market niches established by the very firms operating on the platform (Foerderer, Kude, Mithas, & Heinzl, 2018; Zhu & Liu, 2018; Shi, Aaltonen, Henfridsson, & Gopal, 2023). Consequently, firms operating on platforms face a competitive landscape characterized by endemic uncertainty that is embedded in the governance of the platform itself (Curchod et al., 2020; Rietveld, Ploog & Nieborg, 2020).

2.2 Responding to Platform Dependence: From External Strategies to Internal Responses

Theories of power imbalances in organizational settings (Emerson, 1962; Pfeffer & Salancik, 1978; Casciaro & Piskorski, 2005) are important to explain how firms operating on platforms may manage or circumvent the risks associated with their dependence. Organizations, in fact, do not passively submit to the demands of powerful actors in their environment, but rather develop a variety of strategies to rebalance the power asymmetries they face (Hillman, Withers, & Collins, 2009). Recent platform scholarship has highlighted different strategic paths to navigate dependence, conceptualizing complementor responses in terms of how they reshape their relationships with focal platforms over time (Liu, Henfridsson, Hummel, & Nandhakumar, 2025; Kude & Huber, 2025). For instance, firms can attempt to reduce reliance on a single platform through multihoming strategies or cultivating alternative channels to reach their customers (Kude & Huber, 2025; Gastaldi et al., 2023), forming alliances with other firms operating on the platforms (X. Chen et al., 2024), or evoking government intervention. In other cases, firms may develop tactics that create more room for action by violating the platform's rules, via, for instance, algorithmic manipulation, fake reviews, or disintermediation (Gu, 2024; He, Hollenbeck, & Proserpio, 2022; Balsiger et al., 2023).

While this growing body of work is important for understanding the dynamic and sometimes contentious interplay between platform owners and platform-dependent firms seeking to mitigate power asymmetries, it centers almost entirely on competitive strategies. However, particularly when organizations cannot fully eliminate dependence through market-level strategies, they may rely on internal structural responses to reduce the costs of meeting the demands imposed by powerful actors (Emerson, 1962). One of the main perspectives on the effect of environmental arrangement on changes in the employment structure is ILM theory (Doeringer & Piore, 1971; Baron, 1984; Baron, Dobbin & Jennings 1986). ILM theory posits that organizations strategically use employment structures to respond to changes in their business environment (Allaire & Firsirotu, 1989; Davis-Blake & Uzzi, 1993; Eisenhardt & Martin, 2000). In the next section, we will argue that firms' structural coping mechanisms, particularly their employment decisions, represent an important yet underrecognized response to buffer the uncertainty stemming from platform dependence.

3. Hypotheses development

3.1 Internal Structural Responses: Leveraging Workforce Flexibility to Mitigate Platform Dependence

Previous research underscores the critical importance of internal structural mechanisms in enabling firms to respond to changing environmental demands and effectively buffer uncertainty (Allaire & Firsirotu, 1989; Davis-Blake & Uzzi, 1993). One particularly salient approach concerns the formation of a flexible workforce—often actualized through greater use of NSERs (Atkinson, 1984; Martínez-Sánchez, Vela-Jiménez, Pérez-Pérez, & de-Luis-Carnicer, 2011). NSERs refer to all employment relations other than standard, full-time jobs, and include temporary work, contract labor, independent contractors, and on-call work (Kalleberg, 2000; Pfeffer & Baron, 1988). Substantial research shows that firms turn to NSERs to cope with unstable external conditions, whether driven by cyclical demand, regulatory shifts, or broader market volatility (Davis-Blake & Uzzi, 1993; Pfeffer & Baron, 1988; Uzzi & Barsness, 1998), minimizing long-term commitments and preserving operational agility (Kalleberg, 2000; Mangum, Mayall, & Nelson, 1985). Relatedly, engaging contingent or temporary workers allows firms to quickly address specialized skill gaps without incurring the long-term costs associated with hiring and training permanent staff (Abraham & Taylor, 1996; Matusik & Hill, 1998).

Building on these insights, we argue that reliance on NSERs represents an important yet underrecognized response, particularly well-suited to buffer the structural risks stemming from platform dependence. Reliance on a non-standard workforce allows firms to adjust more rapidly and at lower cost than with a fully permanent workforce, to respond to demand volatility generated by the opacity of platform algorithms (Curchod et al., 2020) and hedge against financial vulnerabilities stemming from it. Also, platform-dependent businesses must frequently respond to technical and operational transitions imposed by the platform owner. For example, the technical resources, such as application programming interfaces (APIs) and software development kits (SDKs), provided to enable engagement with the platform change and evolve over time (Eaton, Elaluf-Calderwood, Sørensen, & Yoo, 2015; Xia et al., 2025). By leveraging temporary workers with expertise in specific platforms or new features, firms can enhance their agility in navigating steep learning curves, ensuring they can adapt and capitalize on, rather than be disadvantaged by the platform's constant changes that may negatively impact their businesses (Ozalp, Cennamo, & Gawer, 2018). Based on these arguments, we hypothesize that:

Hypothesis 1. *Ceteris paribus, firms that use digital platforms are more likely to rely on non-standard employment relationships than comparable firms that do not.*

3.2 Dependence contingencies and heterogeneity among platform participants

Our theorizing suggests that the positive association between platform adoption and reliance on NSERs reflects a coping response to the risks endemic to the techno-economic dependence characterizing digital platforms. However, not all firms are exposed to the same level of dependence, as their degree, and therefore the intensity of responses, varies with structural and strategic factors that affect the balance of power between the actors involved (Emerson, 1962; Pfeffer & Salancik, 1978; Casciaro & Piskorski, 2005). We therefore expect that the strength of the relationship between platform adoption and NSERs will vary with factors that amplify or attenuate a firm's dependence on the platform. We examine four contingencies discussed in the literature and grounded in this logic: firm size and multihoming as *dependence-attenuating* factors, and engagement with dominant platforms and platform-specific investments as *dependence-amplifying* factors.

Dependence-attenuating factors: Firm size

Firm size is a well-established determinant of bargaining power in inter-organizational relationships (Pfeffer & Salancik, 1978). In the platform context, smaller firms tend to have lower bargaining power vis-à-vis the platform, which limits their ability to negotiate more favorable commissions and shields them less from exploitative platform behaviors (Balsiger et al., 2023; Uzunca, Sharapov, & Tee, 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 and greater resources to develop proprietary digital channels. For instance, in 2019, Hilton's president and CEO, Chris Nassetta, announced that 75% of Hilton's overall business originated from its direct channels, thereby making it less reliant on external platforms. This suggests that a stronger positive association between platform adoption and NSER reliance should be more pronounced among smaller firms, given their comparatively limited capacity to resist or mitigate platform power.

Hypothesis 2a. *Firm size moderates the relationship between platform adoption and reliance on non-standard employment relationships, so that the effect is weaker for larger firms than for smaller firms.*

Dependence-attenuating factors: Multihoming

The cultivation of alternative channels to access resources, including customers, is a primary strategy for reducing dependence (Emerson, 1962). In the platform context, multihoming, simultaneously operating on multiple platforms (Cennamo, Ozalp, & Kretschmer, 2018), is the most direct instantiation of this principle. By diversifying across platforms, firms reduce their exposure to the governance decisions of any single platform: if one platform raises fees or changes its algorithm, a multihoming firm can partially absorb the negative impact through its other channels (Cutolo & Kenney, 2021; Gastaldi et al., 2023; Kude & Huber, 2025). This diversification should reduce the platform-specific uncertainty that drives reliance on NSERs. Accordingly, we anticipate that firms engaging with multiple platforms will exhibit a weaker relationship between platform adoption and NSER reliance.

Hypothesis 2b. *Multihoming moderates the relationship between platform adoption and reliance on non-standard employment relationships, such that the effect is weaker for firms using multiple platforms than for those operating on a single platform.*

Dependence-amplifying factors: Engagement with a dominant platform

Another key factor influencing firms' experience of platform-induced dependence is the competitive dynamics of the platform market. The severity of dependence and the intensity of power rebalancing responses increase with the concentration of resource control (Emerson, 1962). When a single platform occupies a dominant market position, firms face a particularly acute form of dependence: the platform's market power reduces the credibility of exit threats, limits the effectiveness of multihoming (because most customers are concentrated on the dominant platform), and gives the platform greater latitude to extract rents or impose unfavorable conditions. 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). Accordingly, we expect that firms engaging with dominant platforms will face higher dependence, hence stronger need for internal buffering through NSERs.

Hypothesis 2c. *Engagement with a dominant platform moderates the relationship between platform adoption and reliance on non-standard employment relationships, such that the effect is stronger for firms using dominant platforms than for those operating on other platforms.*

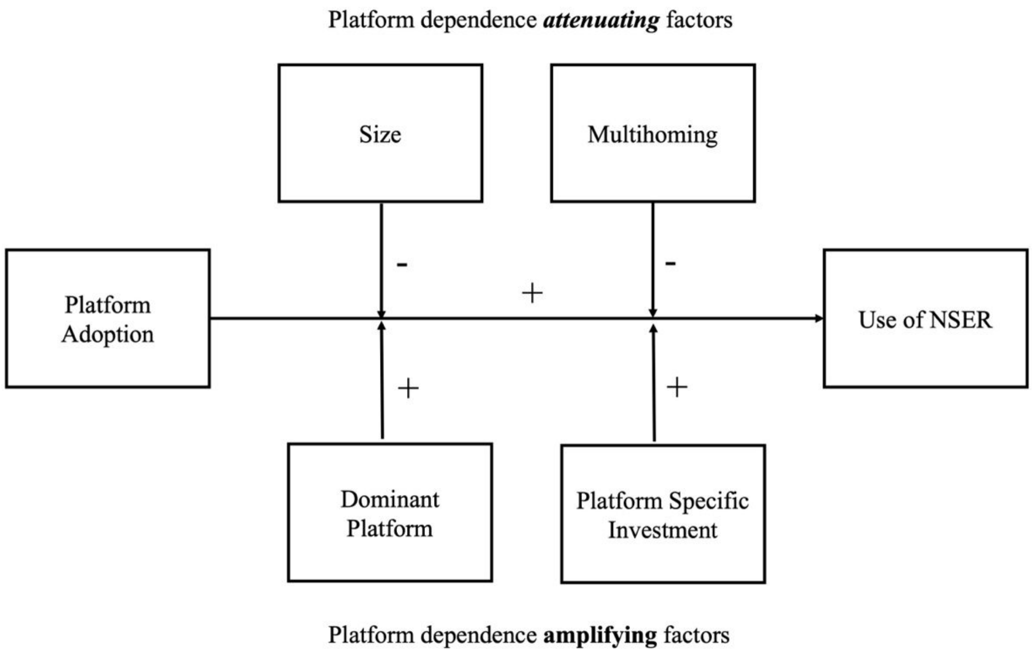
Dependence-amplifying factors: Platform-specific investments

Relationship-specific investment is a central element in theories of inter-organizational dependence (Hart, 1995; Williamson, 1985). Platform adoption often requires specific investments, such as acquiring specialized technological knowledge, investing in certifications, or in platform-specific promotions (Engert, Evers, Hein, & Krcmar, 2022; Wareham, Fox, & Cano Giner, 2014). For instance, in the hotel industry, companies often need to purchase specialized software (e.g., channel managers) with direct interfaces to specific platforms. Similarly, in the restaurant industry, companies can buy cost-per-click advertising tools that help them appear in high-visibility placements across various apps. These investments, while important for supporting a firm's performance on a specific platform, become significantly less valuable outside that platform. Such investments deepen lock-in and raise the costs of exit, thereby amplifying the firm's dependence on the platform and increasing its vulnerability to unilateral governance changes (Dyer, Singh, & Hesterly, 2018). Consequently, we expect a stronger correlation between platform use and NSERs reliance in the presence of platform-specific investments.

Hypothesis 2d. *Platform-specific investments moderate the relationship between platform adoption and reliance on non-standard employment relationships, such that the effect is stronger for firms that make such investments than for those that do not.*

To summarize, our theoretical framework yields a two-tiered set of predictions grounded in power-dependence theory. At the first tier, we predict that platform adoption is associated with higher reliance on NSERs as a response to platform dependence. At the second tier, we predict that the strength of this association varies with factors that modulate the intensity of dependence: it is attenuated when firms possess countervailing resources (larger size, H2a) or access to alternative resource sources (multihoming, H2b), and amplified when dependence is deepened by concentrated platform power (dominant platform, H2c) or elevated switching costs (platform-specific investments, H2d). Figure 1 summarizes our research model.

Figure 1 – Research model



4. Data and Methods

4.1 Setting the scene: the Italian case

To test our hypotheses, we focus on the Italian restaurant and hotel industries. This setting is particularly suitable for testing our theoretical arguments for two reasons. First, Italy has recently experienced a rapid and extensive diffusion of digital platforms, especially within service sectors. In these industries, platforms provide several essential functions, such as reservation management, reviews, payment services, and last-mile logistics (Balsiger et al., 2023; Fradkin, 2017; Guarascio & Sacchi, 2018). As platforms have become increasingly central within these industries, firms increasingly face substantial operational and financial dependence on the platform owners' 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 (Balsiger et al., 2023; Collison, 2020; Stark & Vanden Broeck, 2024). Second, over the past two decades, Italy has experienced significant growth in NSERs, facilitated by regulatory changes that expanded the types of non-standard contracts and relaxed the restrictions on their use (Barbieri & Scherer, 2009). Both the restaurant and hotel industries rely heavily on NSERs, partly because demand is highly seasonal. These two features, substantial platform adoption and the widespread use of NSERs, make the Italian restaurant and hotel industries a suitable empirical context for examining how firms adapt their employment strategies in response to platform dependence.

4.2 Data source: The Digital Platform Survey

We use a unique data source, the Digital Platform Survey (DPS) conducted in 2022 by the Italian National Institute for Public Policy Analysis (INAPP). The DPS provides comprehensive data on the entire population of businesses operating in the restaurant and hotel industries. Specifically, the DPS includes detailed information on firms' access to digital markets, their relationships with platforms or in-house digital infrastructures, as well as performance indicators, organizational characteristics, and the quantity and quality of employment among the surveyed firms[1]. After excluding firms with no employees and those that have existed for less than one year, the final sample comprises 20,638 firms[2]. These operate in the hotel industry—hotels, tourist resorts, guesthouses, and bed-and-breakfasts (B&Bs)—as well as in the restaurant sector, including full-service restaurants and take-away food establishments. Of these firms, 6,920 (33.5%) have been using digital platforms to sell goods and services for at least one year. More specifically, the dataset comprises 13,739 observations in the restaurant industry (1,650 of which use platforms, representing 12%) and 6,899 observations in the hotel industry (5,270 of which use platforms, representing 76.4%).

DPS data are combined with geographic information from the Italian Statistical Atlas of Municipalities (ASC-Istat) and the Italian Ministry of Economy and Finance (MEF), enabling the inclusion of key structural features (e.g., population density, geographic and urban characteristics) as well as variables capturing municipality-level economic dynamics[3].

4.3 Variables

Dependent variable

Our dependent variable is the share of non-standard employment relationships in total employment. Following prior work, NSERs are defined as those resulting from three contract types: fixed-term, collaboration, and on-call (Pfeffer & Baron, 1988).

Independent variables

Our main variable of interest, a firm's adoption of a digital platform, is operationalized as a dummy variable derived from a single survey item (see the Appendix for a detailed description of the survey

[1] For few structural and performance-related variables—such as firm turnover, number of employees, and the number of labour contracts distinguished by type—data were also collected retrospectively (i.e., firms are asked to provide information relating to the previous three-year period) for 2019 and 2020. Investment data, including a breakdown by investment category, were likewise collected retrospectively, but only for 2020. All other information refers to 2021.

[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. Additional analyses (available upon request) confirm that our results hold when 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.

items). It takes the value 1 if a firm relies on a digital platform to sell its goods/services, and 0 otherwise. The latter indicates either no use of digital channels or the use of proprietary digital channels.

Given the predominance of small and medium-sized enterprises (SMEs) in our context, we used the classification developed by the OECD and operationalized *firm size* as a categorical variable based on the number of people employed in 2020: micro firms (fewer than 10 employees), small firms (10–49 employees), and medium-large firms (50 or more employees)[4].

Multihoming is captured by a dummy variable that is equal to 1 for firms that report using more than one platform, based on a dedicated survey item (reported in the Appendix), and 0 otherwise. The same DPS item is used to identify firms that use a *dominant platform*. As DPS firms report not only whether they use digital platforms and how many, but also identify these platforms by name and rank them by their importance to operations, we build a variable that takes the value 1 if a firm uses the dominant platform, i.e. the one that is mostly mentioned as the main platform adopted (e.g., JustEat in the restaurant industry and Booking in the hotel industry)[5] and 0 otherwise.

Finally, *platform-specific investments* is captured using a dedicated DPS item where firms are asked whether they made investments directly related to their platform activities. Hence, we operationalize a dummy variable assuming a value of 1 if firms have realized this type of investment, and 0 otherwise.

Control variables

We included various control variables aimed at capturing firm-level structural characteristics that may systematically affect their likelihood of relying on NSERs, including *size*, *age*, and *subsector* (hotel, resort, B&B, restaurant, or take-away) as identified by distinct ATECO codes[6]. In addition, we include performance variables, such as *investment per employee*, computed as total investment (in euros) divided by the number of employees in 2020. Given that a detailed breakdown of investments is available, we further control for specific categories related to digitalization and advertising (i.e.,

[4] Medium and large firms are combined into a single category due to the limited number of large firms in the sector under investigation (i.e., firms with more than 250 employees).
[5] Platforms exceeding 1% of companies' responses are reported in Table 1.
[6] ATECO codes map onto the NACE classification, providing granular industry detail up to the fifth digit. Firm size is also included as a continuous variable in all regressions.

software, IT, marketing and R&D, trademarks). This allows us to mitigate potential confounding factors and to ensure that the estimated effect of platform use is not simply capturing broader digitalization processes. Beyond investments, additional performance variables include log turnover in 2020, as well as changes in turnover and growth in the log number of employees between 2019 and 2021.

Geographical variables are included to capture territorial characteristics likely to affect both the use of NSERs as well as platform adoption. The localisation of firms is distinguished by seaside, island, or mountain areas/municipalities; while the degree of urbanisation (a factor that may be significantly correlated with the presence of digital platforms) is measured using a three-tier categorical variable (urban, semi-peripheral, rural) and accounting for municipal population density. Finally, economic conditions and related cross-municipality structural heterogeneities are taken into account by including the log average municipal income and the average income from rents. The full list of variables and a set of descriptive statistics distinguishing between platform-using and non platform-using firms are reported in Table 1; while a correlation matrix including all continuous variables is provided in the Appendix (Table A.1).

Table 1 – Variables and descriptive statistics

	Total	No platform use	Use of platforms
Observations	20,638	13,718 (66.5%)	6,920 (33.5%)
Workforce-related variables			
Number of employees (firm-level avg.), 2019	8.4 (26.6)	7.1 (22.1)	11.1 (33.9)
Number of employees (firm-level avg.), 2021	8.1 (26.4)	6.6 (18.7)	10.7 (37.1)
Non-standard contracts (avg. 0-1 share by firm), 2019	0.33 (0.37)	0.31 (0.36)	0.35 (0.38)
Non-standard contracts (avg. 0-1 share by firm), 2021	0.31 (0.36)	0.30 (0.35)	0.34 (0.37)
Firm-level variables			
Firm size (Log # of employees, 2020)	1.6 (0.8)	1.6 (0.7)	1.7 (0.9)
Firm age (# of years since establishment)	16.5 (13.2)	16.1 (12.7)	17.3 (14.1)
Sectors (% of firms by sector)			
Hotels	18.3%	6.3%	42.1%
Resorts	0.7%	0.5%	1.1%
B&Bs	14.5%	5.1%	33.0%
Restaurants	55.5%	73.6%	19.8%
Take-aways	11.0%	14.5%	4.1%
Legal incorporation of the firm (% of firms by type)			
Individual enterprise	37.8%	42.0%	29.6%
LLCs, LLPs	60.8%	56.9%	68.6%
PLCs, Inc.s	0.5%	0.2%	1.0%
Cooperatives	0.9%	0.9%	0.8%
Consortia and others	0.1%	0.1%	0.1%
Firm performance			
Use of own website (% of firms)	39.6%	22.1%	74.3%
Log investments per capita, 2020	2.1 (3.4)	1.8 (3.1)	2.7 (3.8)
Log R&D and marketing investment per capita, 2020	0.1 (0.9)	0.1 (0.8)	0.2 (1.2)
Log trademark investment per capita, 2020	0.1 (0.4)	0.1 (0.4)	0.1 (0.5)

Log IT investment per capita, 2020	0.5 (1.5)	0.4 (1.4)	0.6 (1.8)
Log software investment per capita, 2020	0.1 (0.8)	0.1 (0.6)	0.2 (1.1)
Log turnover per capita, 2020	9.6 (1.9)	9.6 (1.9)	9.7 (2.0)
Log rate of turnover change, 2019-2021	-0.3 (1.9)	-0.3 (1.9)	-0.3 (2.0)
Log employees change, 2019-2021	-0.1 (0.3)	-0.1 (0.3)	-0.1 (0.3)
Geographical variables			
Economic conditions (avg. by municipality)			
Log income per capita, 2021	9.9 (0.2)	9.9 (0.2)	9.9 (0.1)
Log rent per capita, 2021	7.2 (0.5)	7.1 (0.4)	7.3 (0.4)
Territorial characteristics (% of firms by area)			
Urban	27%	24.3%	32.4%
Semi-peripheral	43.8%	46.6%	38.4%
Rural	29.2%	29.1%	29.2%
Mountain	14%	12.6%	16.7%
Beach	37.4%	34.2%	43.6%
Island	1.1%	0.9%	1.5%
Coastal	41.3%	38.7%	46.2%
Macro-region (% of firms by macro-region)			
North-West	20.1%	20.9%	18.5%
North-East	26.3%	25.2%	28.4%
Center	22.2%	22.1%	22.5%
South and Islands	31.4%	31.8%	30.6%
Platform-related variables			
OECD size classes (% of firms in each class)			
Micro-firms (0-9 employees)			78.2%
Small firms (10-49 employees)			19.3%
Medium-large firms (50+ employees)			2.5%
Multihoming (% of firms relying on multihoming)			42.5%
Key platforms in the restaurant industry (% of firms reporting as main platform)			
Just Eat			24.8%
Deliveroo			18.8%
Glovo			6.6%
The Fork			6.7%
Others			43.0%
Key platforms in the hotel industry (% of firms reporting as main platform)			
Booking			89.0%
Airbnb			4.1%
Expedia			0.8%
Others			6.1%
Platform-specific investments (% of firms reporting platform-specific investments)			30.1%

Note: Standard deviation is reported for continuous variables, while percentages are reported for factor variables.

Table 1 shows that firms using digital platforms rely slightly more on non-standard work (34%) than those that do not (30%). Notably, platform-using firms employ nearly twice as many workers on fixed-term and collaboration contracts, and more than four times as many on on-call contracts. Concerning structural characteristics (size, age), no particular differences are detected, and the same holds for economic performance variables. In turn, hotels and B&Bs seem to rely on platforms significantly more than restaurants and takeaway establishments. Platform-using firms report slightly higher per-capita investment levels, regardless of investment type, including R&D, trademarks, IT equipment, and software. As expected, platform-using firms are predominantly located in urban areas, as well as in coastal and mountain regions where tourism plays a significant role. Regarding the most significant platforms, in the restaurant sector, JustEat and Deliveroo hold the largest shares (25% and 19%, respectively), followed by Glovo and The Fork[7]. When it comes to the hotel industry, the market turns out to be far more concentrated, with Booking.com holding a dominant share (89%), followed at a large distance by Airbnb (4.1%) and Expedia (0.8%).

5. Empirical strategy

Our empirical strategy is based on a two-step approach. First, we test whether (and to what extent) firms using platforms employ a higher proportion of NSERs compared to firms that do not use platforms. Second, we explore the underlying mechanisms driving this relationship, focusing only on firms that use platforms to reach their customers and investigating the role of dependence-attenuating and dependence-amplifying factors, as illustrated in Figure 1.

5.1 Testing the relationship between NSERs and platform adoption

As a first step, we estimate the share of NSERs in company i as a function of platform use (i.e., whether company i relies on online platforms or not), a vector X_i of firm-level controls, and a vector Γ_m of

[7] It should be noticed that while JustEat, Deliveroo, and Glovo are all food-delivery platforms, The Fork provides booking and advertisment services.

geographical controls (see Table 1). Given that our dependent variable takes values between 0 and 1, we employ a fractional probit model (Papke & Wooldridge, 1996; Villadsen & Wulff, 2021), relying on the following specification:

$$Nonstandard\ employment\ relationships_{i,2021}$$
$$= \alpha_0 + \beta_1 Use\ of\ Plat_i + \beta_2 X_{i,\,2020} + \delta_s + \theta_r + \Gamma_m + \epsilon_i \ (1)$$

$Nonstandard\ employment\ relationships$ in company i defined as the share of fixed-term, collaboration, and on-call employees over the total number of employees in 2021, serve as the dependent variable. $Use\ of\ Plat_i$ is our main explanatory variable, capturing whether the firm used a online digital platform for sales in 2020 (1 if yes, 0 otherwise). All firm-level control variables are included in X_i in equation (1), with $\beta_2$denoting the corresponding coefficients.

Equation (1) also includes sub-sector fixed effects (δ□)—distinguishing among hotels, resorts, B&Bs, full-service restaurants, and takeaway-only establishments—as well as macro-regional dummies (θ_r) and geographical variables Γ_m. The inclusion of geographical variables requires the use of appropriate clustering to avoid Moulton bias (Moulton, 1990). Accordingly, standard errors are clustered at the municipal (*m*) level, as municipal-level variables are continuous. The term ϵ_i denotes the idiosyncratic error component, capturing residual variation not explained by the model.

After estimation, marginal effects are calculated to retrieve the predicted variation in the dependent variable.

5.2 Testing the role of dependence contingencies

As a second step, we estimate equation (2), focusing exclusively on companies using digital platforms and concentrating on contingencies we expect to either mitigate or amplify firms' dependence on platforms.

$$Non\ standard\ employment\ relationships_{i,2021} = \alpha_0 + \beta_1 Contingency_i + \beta_2 X_{i,2020} + \delta_s + \theta_r + \Gamma_m + \epsilon_i \ (2)$$

The variable $Contingency$ alternately takes the value of 1 in the following cases: if the 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 (1), as well as sub-sectors δ_s and macro-regional θ_r dummies. In the Appendix, we report the estimates of Equation (2) for the full sample, including both firms using digital platforms and those not using platforms. As for the main equation, marginal effects are calculated after estimation to retrieve predicted variations in the dependent variable.

6. Results

Consistent with our argument that platform adoption induces firms to buffer dependence-related uncertainty through workforce flexibility, platform adoption is positive and statistically significant across all specifications (Table 2), indicating that, after controlling for market volatility, geographic controls, and other factors, firms adopting 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 adoption of platforms to reach customers is associated with a 1.7 percentage-point increase in the share of NSERs on average, as indicated by average marginal effects.[8] It is worth noting that including the log change in turnover and the number of employees over the 2019–2021 period as control variables does not affect the significance of the main variable. The coefficients for the log changes in turnover and employees are positive and statistically significant (see Table A.2 in the Appendix)—indicating, as expected, that demand dynamics influence firms' decisions regarding NSERs—however, this does not affect the significance of platform adoption as an additional driver.

[8] Due to the inclusion of a wide set of variables, we controlled for multicollinearity using variance inflation factors (VIFs). Results show a mean VIF of 1.9, well below the traditional threshold of 5 (Cohen et al., 2015), and the highest VIF value does not exceed 7.06. Thus, multicollinearity is unlikely to influence our analyses.

Table 2 - Effect of platform adoption on the firm-level share of non-standard employment relationships

	(1)	(2)
Use of platforms	0.0891***	0.0509*
	(0.0152)	(0.0220)
Firm-level controls	No	Yes
Geographic controls	No	Yes
Constant	-0.513***	3.307**
	(0.00871)	(1.019)
Observations	20,472	20,331
χ^2	34.56	1563
Pseudo R^2	0.000837	0.0468
Base log-likelihood	-12749	-12663
Log-likelihood	-12738	-12070
Number of clusters		4132

Note: p-value: *** p<0.001, ** p<0.01, * p<0.05. Robust standard errors in parentheses. Standard errors are clustered at the municipality level.

Figure 2 – Marginal prediction for the share of NSERs in platform and non-platform firms

Among platform-using firms, reliance on NSERs varies systematically with dependence-relevant contingencies (Table 3). As hypothesized, we find that medium-large firms are less likely than any other type of firm to rely on NSERs ($\beta = -0.502$, $p < 0.001$). Specifically, medium-large firms exhibit, on average, a 13.2 percentage-point lower share of NSERs than small firms (the baseline category), holding other factors constant, as indicated by the estimated average marginal effects, thus supporting Hypothesis 2a. By contrast, the coefficient for micro-firms is positive and significant, indicating a predicted share of NSERs of 35% based on marginal effects (Figure 3), which is 7.4 percentage points higher than the baseline category.

Consistent with H2b, multihoming firms exhibit lower NSER shares than single-homing firms (Model 4), supporting the argument that this strategy reduces dependence on any single platform and, consequently, diminishes the need to rely on NSERs as an adaptive response. On average, holding other factors constant, multihoming firms exhibit a 2.3 percentage-point lower share of NSERs than firms adopting a single platform.

Hypothesis 2c is also supported: reliance on dominant platforms (i.e., JustEat in the restaurant sector [Model 5a] and Booking in the hotel industry [Model 5b]) is associated with a higher share of NSERs relative to platforms with smaller market shares[9]. However, the coefficient is statistically significant only for the hotel industry, where companies using the market-leading platform Booking.com exhibit a 5% higher share of NSERs than those using other platforms, according to the estimated average marginal effects. The significant effect among firms in the hotel industry likely reflects the deeper functional dependence that arises when a dominant platform integrates a broader range of functions. In the restaurant industry, platforms tend to specialize in specific functions (e.g., Yelp for reviews, The Fork for reservations, and Takeaway for delivery). In hotel industry, instead, functional integration prevails (e.g., Booking.com integrating marketplace, reviews, and reservations),

[9] As specified in Section 4.2, 'dominant platforms' are identified at the sectoral level (hotel or restaurants) by determining which platforms are most frequently reported as the primary platform with which firms operate.

and the costs of unilateral governance changes cascade across more operational dimensions, intensifying the need for internal buffering.

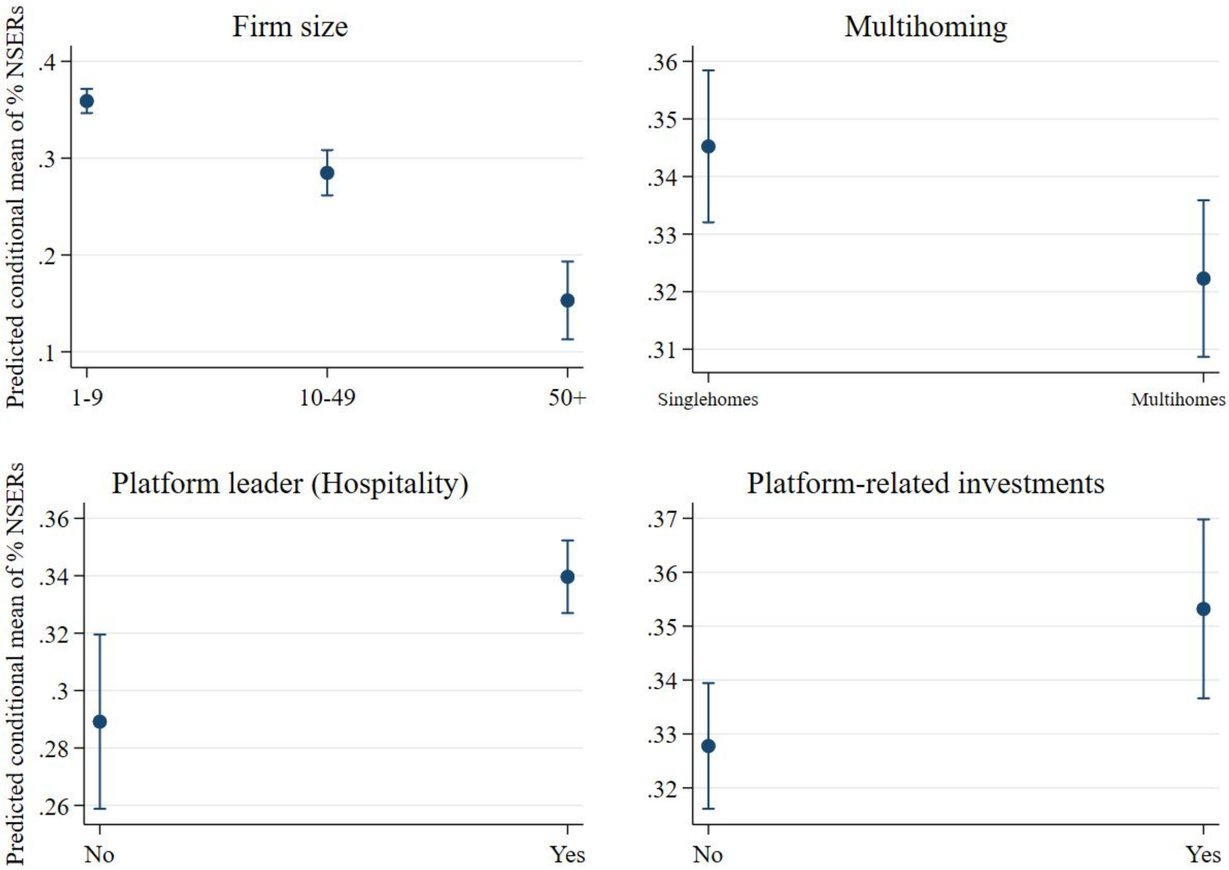
Lastly, platform-specific investments are associated with a higher NSER share (Model 6). On average, holding other factors constant, firms that made platform-specific investments exhibit a 2.5 percentage-point higher share of NSERs than platform-adopting firms that did not undertake such investments, as indicated by the estimated average marginal effects. This supports Hypothesis 2d, corroborating our argument that platform-specific investments may create a lock-in effect that amplifies dependence, leading to greater reliance on NSERs as an adaptive response. Overall, our results support Hypotheses 2a-d, showing that specific firm attributes, either attenuating or amplifying platform dependence, can influence the intensity of internal responses to platform adoption.

Table 3 - Effect of platform dependence contingencies on the firm-level share of non-standard employment relationships

	(3)	(4)	(5a) Restaurants	(5b) Hotels	(6)
Firm size: Micro-firms	0.229***				
	(0.0489)				
Medium-large firms	-0.502***				
	(0.0794)				
Multihoming		-0.0677**			
		(0.0257)			
Using platform market leader			-0.00934	0.156**	
			(0.0503)	(0.0519)	
Investments on the platform					0.0745**
					(0.0271)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes
Constant	3.702*	4.141**	1.953	4.820**	4.333**
	(1.465)	(1.471)	(2.128)	(1.624)	(1.476)
Observations	6,830	6,830	1,622	5,208	6,830
χ^2	829.4	826.5	122.9	760.0	822.9
Adjusted R^2	0.0675	0.0652	0.0238	0.0862	0.0653
Base log-pseudolikelihood	-4358	-4358	-1037	-3321	-4358
Log-pseudolikelihood	-4064	-4074	-1013	-3035	-4074
Number of clusters	1788	1788	691	1474	1788

Note: p-value: *** p<0.001, ** p<0.01, * p<0.05. Robust standard errors in parentheses. Standard errors are clustered at the municipality level. Base category for firm size is small firms.

Figure 3 – Marginal prediction for the share of NSERs in platform firms – Dependence-attenuating and dependence-amplifying factors



6.1 Robustness checks

Our results hinge on firms' decisions to adopt online sales platforms, which may be influenced by observable and unobservable characteristics. To address endogeneity concerns, we implement several robustness checks. The first test addresses issues of self-selection into treatment, which could potentially bias the estimates. In fact, the decision to adopt platforms is endogenous to many firm-level characteristics (e.g., level of digitalization of the firm, significance of digital markets, etc.). We thus rely on Coarsened Exact Matching (CEM) to match and compare firms that are similar in all respects except for the use of digital platforms (Iacus, King & Porro, 2012).[10] As column 1 in Table 4 reports, β_1 remains positive and statistically significant, indicating a 2.6 percentage-point higher share of NSERs among platform-using firms compared to similar firms not using platforms (Figure A.2 in the Appendix).

Second, to rule out the possibility that our results are affected and biased by the COVID-19 pandemic, we used the share of non-standard employment in 2019 as the dependent variable and included a subset of controls referring to 2019. Model 2 in Table 4 replicates our findings by focusing on the pre-COVID period. The estimates remain consistent, thereby confirming Hypothesis 1 (Figure A.3 in the Appendix).

Table 4 – Effect of platform adoption on the share of unstable workers: CEM and pre-COVID estimates

	(1)	(2)
Use of platforms	0.0831**	0.0659*
	(0.0320)	(0.0273)
Firm-level controls	Yes	Yes
Geographic controls	Yes	Yes
Constant	7.472***	4.036***
	(2.023)	(1.084)
Observations	15,183	16,715
χ^2	556.5	1002
Pseudo R^2	0.0794	0.0542
Base log-likelihood	-9204	-10448
Log-likelihood	-8473	-9882
Number of clusters	2950	3873

Note: p-value: *** p<0.001, ** p<0.01, * p<0.05. Robust standard errors in parentheses. Standard errors are clustered at the municipality level.

[10] A key concern is that, ideally, we would compare employment decisions between highly similar firms on and off digital platforms. However, platform adoption is not random, and firms operating on platforms are likely to differ systematically from those that do not. To strengthen the validity of our results, we restrict the analysis to firms within the common support obtained after a matching procedure. Firms were matched based on the following characteristics: size class (0–5, 6–15, 16–50, 51+ employees), geographical area (North-West, North-East, Center, South, Islands), population density, per-capita municipal income in 2021 (logarithmic), per-capita municipal rent in 2021 (logarithmic), urban, rural, mountain, and coastal/beach areas, and subsector (hotels, B&Bs, restaurants, take-aways).

Third, to address potential risks of reverse causality—i.e., organizational flexibility associated with the use of NSERs driving platform adoption—we estimate a *difference-in-differences (DiD)* model with CEM-matched controls and firm fixed effects, focusing on firms that started using platforms during the COVID-19 pandemic. Considering the latter as an exogenous shock[11] (i.e., in the absence of the pandemic, treated firms would have been just as likely to rely on digital platforms as their matched peers), the DiD model reduces the risk that the observed relationship is driven by idiosyncratic characteristics of the treated firms or by reverse causality.

We leverage the availability of information on turnover, personnel, and contractual relationships for three years (2019, 2020, and 2021), to build a three-year firm-level panel (see also Table A.5 in the Appendix). As the remaining covariates are time-invariant, they are incorporated into the matching process but are otherwise absorbed by the difference-in-differences structure of the model. As argued, the COVID-19 pandemic can be regarded as an exogenous shock likely to accelerate firms' entry into the platform economy, thereby providing a natural setting for counterfactual analysis. Within this framework, treated firms are those that adopted platforms in 2020, while the control group comprises otherwise similar firms that did not adopt. 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 pre-treatment share of NSERs in 2019 and 2020. This approach aims to ensure that the matched firms follow similar trajectories prior to platform adoption (see Figure A.1 in the Appendix). This procedure assigns weights to control observations and excludes those lying outside the common support, that is, firms too dissimilar from adopters to serve as valid controls. We then estimate a DiD model with firm and year fixed effects to account for potential unobserved heterogeneities.

Formally, the following equation has been estimated:

[11] It is well established that the COVID-19 pandemic prompted many businesses to rapidly digitalize their sales channels (Lee, Yang, Ghauri, & Park, 2021). This trend was particularly evident in the restaurant sector, where many operators explored alternative avenues to implement delivery systems. Among these, the adoption of digital food delivery platforms became especially prominent, as they provided both a sales channel and access to delivery personnel (Pirone, Frapporti, Chicchi, & Marrone, 2020; Ravenelle, Kowalski, & Janko, 2021).

$$NonStandardEmploymentRelationships_{i,t} = \beta_1 Use\ of\ Plat_i + \beta_2(Use\ of\ Plat_i \cdot 2021) + \beta_3(Use\ of\ Plat_i \cdot 2019) + \alpha_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

where $NonStandardEmploymentRelationships_{i,t}$ captures the share of NSER for each firm i in year t=2019, 2020, 2021. Our key explanatory variables, $Use\ of\ Plat_i$ is a dummy taking value of 1 whether the firm 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, with 2020 as the omitted-based year. The interaction term $Use\ of\ Plat_i \cdot 2021$ measures the *DiD* effect, i.e., the differential change in NSER between 2020 and 2021 for adopters relative to non-adopters. The interaction $Use\ of\ Plat_i \cdot 2019$ serves as a placebo term to capture whether adopters and non-adopters already exhibited differential changes between 2019 and 2020, providing a check on the common-trend assumption. Lastly, ϵ_i is an error term clustered at the panel level.

Table 5 reports the results of the DiD estimation. The coefficient 'Use of platforms' × 2021 ($\beta_2 = 0.0183$, $p < 0.05$) shows that, in 2021, firms adopting platforms in 2020 increase their share of non-standard employment relationships by 1.8 percentage points more than comparable non-adopters. By contrast, the coefficient on 'Use of platforms' × 2019 is very small and statistically insignificant, suggesting no differential change between 2019 and 2020 for adopters and non-adopters, which is consistent with the common-trend assumption. Overall, these results indicate that platform adoption is associated with a subsequent increase in the use of non-standard work arrangements, as also illustrated by the average treatment effect on the treated in Figure 1. These findings lend further support to our main argument that reliance on NSERs increases as an adaptive response to the risks stemming from platform dependence.

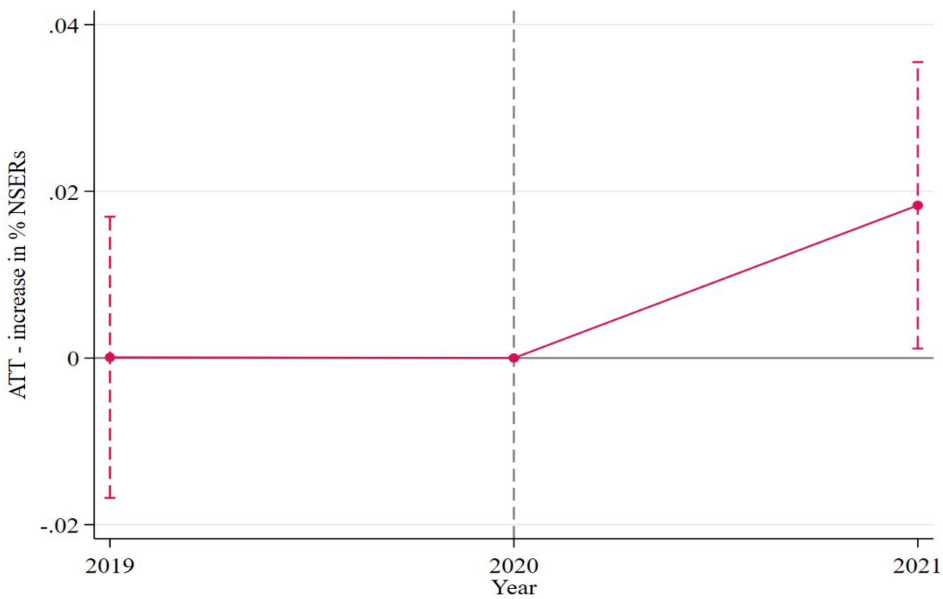
Table 5 - Impact of 2020 platform adoption on non-standard work - Difference-in-Differences with Coarsened Exact Matching

Use of platforms × 2019	8.34e-05
	(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
Within adjusted R^2	0.0164
Adjusted R^2	0.892
Base log-likelihood	17809
Log-likelihood	17967
F-statistic	14.35

Note. p-value: *** p<0.001, ** p<0.01, * p<0.05. Robust standard errors in parentheses. Standard errors are clustered at the panel level. The base year is 2020.

Figure 4 – Average Treatment effect on the Treated Group (Firms using platforms)



Lastly, to rule out the possibility that platform use reflects general employment restructuring rather than a specific buffering response through non-standard arrangements, we examine the relationship between platform use and the share of standard employment relationships (proxied by the share of employees holding open-ended contracts over total employment). Results in Table A.6 show that the relationship between the two variables is non-significant (Column 1). Even after addressing potential endogeneity concerns relying on the CEM (Column 2), the results indicate no significant relationship between stable employment and platform adoption, thereby corroborating our main hypothesis.

7. Discussion

Platforms have become significant forces across an increasing number of industries and economic sectors, developing into the "dominant institutional form of the digital age" (Kenney et al., 2021; Gawer, 2022). Existing research has already shown the transformative impact of platforms' infrastructural power on firms' competitive strategies (Cutolo et al., 2021; Hagiu & Wright, 2021), highlighting the importance of both harnessing a platform's resources and mitigating its power (Kude & Huber, 2025). This study provides the first evidence that platforms also affect firms' internal organization, as firms use employment relationships to buffer the specific risks and uncertainties arising from platform governance. Our analysis indicates that firms using platforms are more likely than comparable businesses not using platforms to rely on NSERs. Critically, these results hold after controlling for demand-volatility measures (turnover and employment change), suggesting that the employment adjustments we observe are not merely a reflection of generic market uncertainty but rather a mechanism to cope with the specific risks these firms may face. These results are further confirmed by a difference-in-differences fixed-effects analysis (Donald & Lang, 2007) combined with coarsened exact matching (Iacus et al., 2012). This strategy allows for estimating the average impact of platform adoption on NSERs, accounting for both unobserved heterogeneity and selection into treatment, thereby strengthening the interpretation of platforms' impact on firms' organizational decisions, even in the short term.

We further demonstrate that this shift can be interpreted as a response to the risks posed by dependence on a powerful platform. Indeed, factors that heighten a firm's dependence on a given platform (e.g., the presence of platform-specific investments or engagement with a dominant platform) and hence the exposure to adverse effects caused by changes in the algorithms, fee structure, or technological requirements, amplify the relationship between platform adoption and the use of NSERs. On the other hand, strategies and resources that reduce platform dependence (e.g., multihoming or firm size) attenuate the effect

Our work makes three important theoretical contributions. First, we contribute to the growing information system literature exploring the challenges faced by existing firms as they interact with and through platforms to deliver their offerings to users (Cutolo & Kenney, 2021; Hänninen & Smedlund, 2021; Kude & Huber, 2025; Zhu & Liu, 2018). This body of work highlights that platform-organized markets are precarious for participants due to intense competitive dynamics (Boudreau, 2012), fast-evolving users' preferences (Panico & Cennamo, 2022; Rietveld & Eggers, 2018), and, perhaps most importantly, the contradictory logics and power asymmetries that characterize their relationship with the platform owner (Curchod et al., 2020; Hurni et al., 2022; Jacobides et al., 2024). In this regard, prior work explicitly recognizes the increasing need for these platform-dependent firms to develop strategic responses that mitigate the vulnerabilities and the risks stemming from platform owners' governance decisions (Gastaldi et al., 2023; Wang & Miller, 2020; Wen & Zhu, 2019). We extend this research by identifying internal organizational design, specifically employment structure, as a central yet unrecognized mechanism through which firms respond to these risks. While prior work has emphasized competitive and market-facing strategies, we show that firms buffer dependence by increasing reliance on non-standard employment relationships (NSERs), shifting the focus from external positioning to internal adaptation.

Our work thus 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, p. 266), pointing to the incompleteness of the extant focus on strategic positioning and competitive decisions to understand the consequences of platform power and the responses of platform-dependent firms (Hurni et al., 2022; Kude & Huber, 2025), and underscoring the need for a more integrated perspective that also takes into account the internal adaptations that firms undertake to operate in platform-mediated markets.

Second, while our findings support the notion that platform adoption constitutes an existential experience of uncertainty for firms due to platform owners' strategies and governance mechanisms (Huber et al., 2017; Curchod et al., 2020; Cutolo & Kenney, 2021), our empirical evidence indicates that platform dependence and its risks are not experienced uniformly. The differential effects observed in our analysis suggest that, although all firms that rely on platforms are, to some extent, exposed to the threat of platform dependence, their responses vary significantly across firms, depending on firm-level characteristics, strategic choices, and contextual conditions. This insight adds to recent research aimed at refining our understanding of the features and circumstances that render firms more or less dependent on platforms (Gastaldi et al., 2023; Kude & Huber, 2025; Rietveld et al., 2020), by suggesting that this dependence is best conceptualized as a multidimensional continuum rather than a singular, monolithic state of precariousness.

Third, this paper offers important insight for studies exploring the impact of platforms on labor (Liu, Pei, & Zhang, 2024; Lin, Lu, Wang, & Kou, 2025; Guo, Cheng, & Pavlou, 2025; Vallas & Schor, 2020). While much has been written about the contingent and precarious nature of platform-mediated labor (Schor & 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 firms using 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 the continuing platformization of the economy 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 adoption, they also raise concerns about broader labor-market implications (Kalleberg, 2000). As platforms continue to mature and become ever more constitutive of the modern economy (Kenney & 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 & Hagiu, 2009), their effects reverberate well beyond their immediate boundaries, affecting industries, labor markets, and society at large (Srnicek, 2017). Understanding this is essential to developing strategies and tools to properly address the distribution of risk and benefits between platform owners and indirect participants, such as workers in firms dependent on platforms (Jacobides & Lianos, 2021).

This brings us to the policy implications of our study. Our findings echo previous work emphasizing the need for well-designed competition policies to limit the power of platforms without compromising the positive effects they have on commerce (Cusumano, Gawer, & Yoffie, 2021; Jacobides & Lianos, 2021). To address techno-economic dependence and its unintended organizational and structural consequences, various policy instruments can be considered. Cross-platform competition could be favored by limiting the share of services (e.g., reservations, marketplace) managed by a single platform in an industry. This would make it easier to multihome, which, as our results show, could reduce the negative externalities generated by platform adoption. Likewise, measures directed at ensuring algorithmic transparency could help prevent platforms from abusing the power stemming from the connection between buyers and sellers of goods and services. In this regard, the EU Digital Markets Act might serve as an effective regulatory anchor. Enacted in early 2024, it requires 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 ensure that such policies are implemented in a timely and effective manner, sector-specific regulatory bodies, including members of employer associations and trade unions, could prove helpful as the nature of firm–platform relationships (and related policy problems) vary significantly across industries.

Moreover, we show that one consequence of platform adoption would be increased adoption of NSERs, which, in turn, may lead to a generalized deterioration in the quality of employment, with potentially negative social and macroeconomic implications. In this respect, labor policy may also play a significant role. Specifically, measures that limit companies' reliance on NSERs could help prevent excessive workforce precarity, especially in industries characterized by high uncertainty. We acknowledge, however, that the efficacy of these policy measures will depend on national labor-law regimes, institutional contexts, and sector-specific dynamics. Our empirical evidence is drawn from a single country (Italy), and two specific industries (hotels and restaurants), and the extent to which these policy implications generalize to other regulatory environments remains an open question. Nonetheless, the pattern we document suggests that policymakers should attend not only to the direct labor effects of platforms (e.g., gig work) but also to these indirect, firm-mediated effects on employment quality.

7.1 Boundary conditions and opportunities for future extensions

Naturally, our 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 our findings generalize to other contexts, cross-country as well as sectoral heterogeneities need to be systematically investigated. Platform dynamics tend to be different depending on the structural and institutional context they face (e.g., the relevance of digital vs. non-digital channels, country- and industry-specific norms protecting non-platform incumbents, data-related regulations imposing algorithmic transparency). Moreover, our buffering mechanism assumes that firms have access to a flexible labor market with available NSER contracts—a condition that varies across national labor-law regimes. In countries with stricter employment protections (e.g., France's CDI/CDD framework), platform-dependent firms may pursue different internal adaptations, such as task restructuring or outsourcing, rather than contract-type substitution. This represents a theoretically meaningful boundary condition, and it would be important to empirically assess how companies' adaptive strategies in platform-organized sectors vary across countries and industries, as well as the influence of factors such as unionization levels, workers' bargaining power, and government interventions. For instance, Spain recently introduced a reform aimed at curbing the use of temporary contracts for workers. Does the presence of different regulations affect the extent to which firms rely on internal adjustment? Such comparative evidence could be useful in providing policy advice. Beyond sector specificities, we can expect that the theoretical mechanisms outlined in this analysis may be generalized to other sectors that have recently experienced similar dynamics, such as firms selling through e-commerce or app-store platforms, though in each sector, there should be specific peculiarities.

Second, while our analysis provides robust evidence accounting for various confounding factors and self-selection, a key improvement would be to strengthen the causal plausibility of our findings. In this regard, the availability of longitudinal data for all companies would be valuable. No less important, longitudinal data over an extended time span would allow for a more dynamic exploration of the firm–platform relationship, accounting for the evolving nature of platform dependence over platforms and firms' life cycle (Cutolo & Kenney, 2021; Rietveld et al., 2020)

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

8. Conclusion

As platforms increasingly consolidate their power as critical intermediaries, understanding how this transformation reshapes societal structures has become a fundamental scholarly priority. This study shows that platform adoption is associated with a systematic shift in how firms organize work internally, suggesting the need to consider platforms' impacts from multiple perspectives, including organizational design and workforce strategies. Drawing on power-dependence theory and internal labor market theory, we argue and find that when firms rely on platforms to access customers, the uncertainty arising from being dependent on a powerful, self-interested actor, increases the value of internal buffering through NSERs. By documenting employment configuration as an internal response to the peculiar risks associated with platform adoption, we extend platform research by highlighting an indirect channel through which platform power can intensify workforce precarity beyond platform-managed gig work. As platforms continue to consolidate their infrastructural role across industries, understanding their impacts therefore requires linking market and competitive dynamics to organizational design choices that shape workers' employment conditions.

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APPENDIX

Tables

Table A.1 –Correlations matrix – Continuous variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
1. Fixed-term, 21	-															
2. Collaboration, 21	0.047	-														
3. On-call, 21	0.021	0.036	-													
4. Employees, 21	0.784	0.111	0.111	-												
5. Firm Size	0.436	0.144	0.083	0.507	-											
6. Firm age	0.046	0.032	-0.001	0.052	0.130	-										
7. Log investment	0.106	0.034	0.014	0.102	0.155	0.055	-									
8. Log R&D investment	0.021	0.036	0.003	0.025	0.045	- 0.009	0.272	-								
9. Log trademark investment	0.121	0.015	0.012	0.107	0.071	0.000	0.140	0.229	-							
10. Log IT investment	0.066	0.017	0.011	0.070	0.084	0.046	0.468	0.225	0.131	-						
11. Log software investment	0.077	0.046	0.005	0.090	0.107	0.016	0.274	0.332	0.206	0.299	-					
12. Log turnover per capita, 20	0.057	0.007	-0.014	0.062	0.115	0.044	0.171	0.024	0.031	0.088	0.046	-				
13. Log income in municipality	0.024	0.016	0.021	0.082	0.139	0.009	0.010	-0.003	0.011	0.033	0.026	0.060	-			
14. Log rent in municipality	0.057	0.035	0.012	0.058	0.080	0.052	0.057	0.017	0.012	0.049	0.040	0.062	0.499	-		
15. Population density	0.026	0.007	0.023	0.083	0.114	-0.080	-0.041	-0.010	0.012	-0.019	0.019	0.009	0.451	0.319	-	
16. Log change in turnover, 19-21	0.026	0.000	0.000	0.017	0.028	-0.018	0.054	0.018	0.011	0.019	0.013	0.157	-0.043	-0.040	-0.038	-
17. Log change in personnel, 19-21	0.068	0.005	0.018	0.053	-0.000	-0.033	0.077	0.032	0.001	0.045	0.014	0.057	-0.042	-0.044	-0.046	0.273

Table A.2 - Effect of platform dependence contingencies on the firm-level share of non-standard employment relationships (full version of Table 2)

	(1)	(2)
Use of platforms	0.0891***	0.0509*
	(0.0152)	(0.0216)
Resorts		-0.151
		(0.0928)
B&Bs		-0.322***
		(0.0357)
Restaurants		-0.0151
		(0.0279)
Take-aways		-0.154***
		(0.0356)
Log rate of turnover change, 2019-2021		0.0245***
		(0.00466)
Log employees change, 2019-2021		0.245***
		(0.0262)
Log of number of employees, 2020 (size)		0.232***
		(0.0148)
Log of number of employees, 2019 (size)		
Firm age		-0.00548***
		(0.000607)
LLCs, LLPs		0.0746***
		(0.0196)
PLCs, Inc.s		-0.368***
		(0.110)
Cooperatives		-0.00622
		(0.0808)
Consortia and others		0.434
		(0.291)
Website		0.113***
		(0.0181)
Log of investment per capita 2020		0.00486
		(0.00260)
Log of R&D and marketing inv. per capita 2020		0.0127
		(0.00796)
Log of trademark investment per capita 2020		0.0330*
		(0.0161)
Log of IT investment per capita 2020		-0.00748
		(0.00529)
Log of software investment per capita 2020		-0.0164
		(0.00924)
Log turnover per capita, 2020		0.00228
		(0.00431)
Log turnover per capita, 2019		
Log income per capita in municipality, 2021		-0.544***
		(0.103)
Log rent per capita in municipality, 2021		0.170***

		(0.0291)
Urban		-0.0928**
		(0.0338)
Rural		0.0103
		(0.0260)
Mountain		0.185***
		(0.0337)
Beach		0.0639
		(0.0444)
Island		0.191*
		(0.0855)
Coastal		0.0170
		(0.0445)
Population density		-4.42e-05**
		(1.50e-05)
North-West		0.0447
		(0.0392)
North-East		0.0637
		(0.0384)
South and Islands		-3.51e-05
		(0.0355)
Constant	-0.513***	3.305***
	(0.00871)	(0.870)
Observations	20,472	20,331
χ^2	34.56	1576
Adjusted R^2	0.000837	0.0468
Base log-pseudolikelihood	-12749	-12663
Log-pseudolikelihood	-12738	-12070
Number of clusters		4132

Robust standard errors in parentheses, p-value: *** p<0.001, ** p<0.01, * p<0.05. Standard errors are clustered at the municipality level. Base categories are: Small firms, Individual enterprise, Semi-peripheral urbanization, Center.

Table A.3 - Effect of platform adoption on the firm-level share of non-standard employment relationships (full version of Table 3)

	(5)	(6)	(7a -Restaurants)	(7b -Hotels)	(8)
Micro-firms	0.229***				
	(0.0476)				
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)
Resorts	-0.00216	-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)	(0.0403)		(0.0427)	(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, 2019-2021	0.0347***	0.0352***	0.0374**	0.0361***	0.0357***
	(0.00790)	(0.00784)	(0.0143)	(0.00908)	(0.00788)
Log employees change, 2019-2021	0.259***	0.262***	0.151*	0.329***	0.263***
	(0.0442)	(0.0443)	(0.0629)	(0.0592)	(0.0445)
Log of number of employees, 2020 (size)	0.308***	0.168***	0.0696**	0.209***	0.161***
	(0.0314)	(0.0185)	(0.0252)	(0.0241)	(0.0184)
Firm age	-0.00215*	-0.00194	-0.00753***	-0.00120	-0.00180
	(0.00102)	(0.00101)	(0.00217)	(0.00118)	(0.00102)
LLCs, LLPs	0.219***	0.246***	-0.0341	0.346***	0.241***
	(0.0398)	(0.0397)	(0.0549)	(0.0496)	(0.0397)
PLCs, Inc.s	-0.132	-0.172	-0.982***	-0.135	-0.193
	(0.134)	(0.135)	(0.285)	(0.144)	(0.134)
Cooperatives	0.0202	0.0727	-0.152	0.171	0.0712
	(0.168)	(0.166)	(0.289)	(0.198)	(0.167)
Consortia and others	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 of investment per capita 2020 with depreciation	0.00339	0.00302	-0.000180	0.00403	0.00269
	(0.00399)	(0.00398)	(0.00758)	(0.00459)	(0.00400)
Log of R&D and marketing investment per capita 2020	0.0126	0.0135	0.00808	0.0152	0.0127
	(0.0115)	(0.0115)	(0.0210)	(0.0137)	(0.0116)
Log of trademark investment per capita 2020	0.0308	0.0290	0.0558*	0.0262	0.0287
	(0.0207)	(0.0206)	(0.0310)	(0.0256)	(0.0206)
Log of IT investment per capita 2020	-0.00428	-0.00533	0.0226	-0.0111	-0.00585
	(0.00864)	(0.00860)	(0.0148)	(0.0104)	(0.00866)
Log of software investment per capita 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 income per capita in municipality, 2021	-0.667***	-0.665***	-0.311	-0.792***	-0.682***
	(0.140)	(0.140)	(0.229)	(0.169)	(0.140)
Log rent per capita in municipality, 2021	0.229***	0.224***	0.108	0.259***	0.220***
	(0.0415)	(0.0416)	(0.0864)	(0.0469)	(0.0412)
Urban	-0.0962	-0.0942	-0.124	-0.0935	-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	0.0542	0.0317	0.0824	0.0536
	(0.0848)	(0.0851)	(0.158)	(0.0997)	(0.0850)
Population density	-4.93e-05**	-4.94e-05**	-3.87e-05**	-5.82e-05*	-5.00e-05**
	(1.87e-05)	(1.83e-05)	(1.48e-05)	(2.89e-05)	(1.83e-05)
North-West	0.0604	0.0550	0.0164	0.0530	0.0578
	(0.0466)	(0.0467)	(0.0817)	(0.0559)	(0.0469)
North-East	0.0738	0.0687	0.0351	0.0782	0.0762*
	(0.0455)	(0.0458)	(0.0776)	(0.0552)	(0.0463)
South and Islands	0.0593	0.0542	-0.00735	0.0611	0.0509
	(0.0488)	(0.0492)	(0.0864)	(0.0584)	(0.0492)
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	795.0
Adjusted 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

Robust standard errors in parentheses, p-value: *** p<0.001, ** p<0.01, * p<0.05. Standard errors are clustered at the municipality level. Base categories are: Small firms, Individual enterprise, Semi-peripheral urbanization, and Center.

Table A.4 - Effect of platform adoption on the share of unstable workers: CEM and pre-COVID estimates (full version of Table 4)

	(1)	(2)
Use of platforms	0.0831**	0.0659*
	(0.0320)	(0.0273)
Resorts	-0.425	-0.127
	(0.228)	(0.0972)
B&Bs	-0.379***	-0.175***
	(0.0670)	(0.0376)
Restaurants	-0.0914	-0.000865
	(0.0525)	(0.0312)
Take-aways	-0.110	-0.0954*
	(0.0688)	(0.0417)
Log rate of turnover change, 2019-2021	0.00522	
	(0.0119)	
Log employees change, 2019-2021	0.161*	
	(0.0756)	
Log of number of employees, 2020 (size)	0.271***	

	(0.0442)	
Log of number of employees, 2019 (size)		0.336***
		(0.0167)
Firm age	-0.00469**	-0.00602***
	(0.00148)	(0.000669)
LLCs, LLPs	0.145**	-0.0146
	(0.0508)	(0.0206)
PLCs, Inc.s	-0.745*	-0.459***
	(0.304)	(0.114)
Cooperatives	-0.0448	-0.118
	(0.204)	(0.0920)
Consortia and others	-0.228	0.174
	(0.448)	(0.280)
Website	0.0542	0.0791***
	(0.0484)	(0.0207)
Log of investment per capita 2020	0.00423	
	(0.00825)	
Log of R&D and marketing inv. per capita 2020	0.0152	
	(0.0152)	
Log of trademark investment per capita 2020	0.00232	
	(0.0372)	
Log of IT investment per capita 2020	-0.00862	
	(0.0128)	
Log of software investment per capita 2020	0.00500	
	(0.0261)	
Log turnover per capita, 2020	-0.00141	
	(0.0129)	
Log turnover per capita, 2019		-0.0165***
		(0.00445)
Log income per capita in municipality, 2021	-0.911***	-0.619***
	(0.215)	(0.111)
Log rent per capita in municipality, 2021	0.0902	0.176***
	(0.0563)	(0.0311)
Urban	-0.0763	-0.106**
	(0.0652)	(0.0397)
Rural	0.0124	0.0184
	(0.0643)	(0.0264)
Mountain	0.298***	0.186***
	(0.0686)	(0.0355)
Beach	0.249**	0.0367
	(0.0860)	(0.0491)
Island	0.447	0.164
	(0.271)	(0.0917)
Coastal	-0.143	0.0501
	(0.0840)	(0.0486)
Population density	-2.43e-05	-3.77e-05*
	(2.51e-05)	(1.49e-05)
North-West	0.0557	0.0310
	(0.0673)	(0.0372)
North-East	0.0616	0.0677
	(0.0661)	(0.0376)
South and Islands	-0.0467	-0.0194
	(0.0657)	(0.0359)
Constant	7.472***	4.034***

	(2.023)	(0.934)
Observations	15.183	16,715
χ^2	556.5	1164
Adjusted R^2	0.0794	0.0542
Base log-pseudolikelihood	-9204	-10448
Log-pseudolikelihood	-8473	-9882
Number of clusters	2,950	3873

Robust standard errors in parentheses, p-value: *** p<0.001, ** p<0.01, * p<0.05. Standard errors are clustered at the municipality level. Base categories are: Small firms, Individual enterprise, Semi-peripheral urbanization, Center. CEM was performed on firm size, sub-industry, and all municipal-level variables. The population for 2019 excludes those firms that are born after 2018. All firms which joined platforms after 2019 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.

Table A.5 – Descriptive statistics for panel sub-sample (Difference in Differences regression) – average over three years of observations

	Total	No platforms	Platform use
Observations	42,588 (100.0%)	40,668 (95.5%)	1,920 (4.5%)
By year (balanced panel)			
2019	14,196	13,556	640
2020	14,196	13,556	640
2021	14,196	13,556	640
Dependent variable			
% Non-standard employment relationships	0.303 (0.355) 42,588	0.301 (0.356) 40,668	0.341 (0.343) 1,920
Firm-level characteristics			
Log turnover per capita	9.703 (1.996) 42,365	9.704 (1.991) 40,456	9.695 (2.097) 1,909
Industry			
Restaurants	37,392	35,877	1,515
Hotels	5,196	4,791	405
Industry sub-sectors			
Hotels	2,733	2,523	210
Resorts	198	189	9
B&Bs	2,265	2,079	186
Restaurants	31,221	29,988	1,233
Take-aways	6,171	5,889	282
Size classes (OECD definition)			

Micro-firms (1-9)	36,183	34,743	1,440
Small firms (10-49)	6,054	5,622	432
Medium-large firms (50+)	351	303	48
Use of own website	9,870	9,009	861
Geographical characteristics			
Beach	14,733	13,896	837
Island	387	363	24
Coastal	16,614	15,744	870
Urbanization level			
Urban	10,782	9,864	918
Semi-peripheral	19,662	18,930	732
Rural	12,144	11,874	270
Area of the country			
North-West	8,949	8,538	411
North-East	10,656	10,266	390
Center	9,423	8,976	447
South and Islands	13,560	12,888	672

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 A.6 - Effect of platform adoption on the firm-level share of stable workers

	(1)	(2)
Use of platforms	0.0403	0.0618
	(0.0217)	(0.0372)
Firm-level controls	Yes	Yes
Geographic controls	Yes	Yes
Constant	-6.960***	-9.395***
	(1.107)	(2.769)
Observations	20,331	15,183
χ^2	1605	857.2
Pseudo R^2	0.0687	0.111
Base log-likelihood	-13428	-9573
Log-likelihood	-12505	-8515
Number of clusters	5549	3773

p-value: *** p<0.001, ** p<0.01, * p<0.05

Robust standard errors in parentheses. Standard errors are clustered at the municipality level.

Table A.7 - Effect of platform dependence contingencies on the firm-level share of non-standard employment relationships – Full sample regressions

	(1)	(2)	(3)	(4)	(5)
Use of platforms	-0.0443	0.0826***	0.0247	-0.0739	
	(0.0354)	(0.0238)	(0.0291)	(0.0579)	
Micro-firms × Platforms	0.127***				
	(0.0377)				
Medium-large firms × Platforms	-0.00939				
	(0.115)				
Multihoming		-0.0842***			
		(0.0251)			
Using platform market leader			0.0533	0.161**	
			(0.0496)	(0.0520)	
No investment on the platform					0.0351
					(0.0224)
Investment on the platform					0.104***
					(0.0303)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes
Constant	2.916***	3.237***	2.540*	4.551**	3.333***
	(0.861)	(0.868)	(1.056)	(1.532)	(0.869)
Observations	20,331	20,331	13,533	6,798	20,331
χ^2	1651	1587	941.1	867.8	1594
Pseudo-R^2	0.0496	0.0471	0.0325	0.0849	0.0470
Base log-likelihood	-12663	-12663	-8373	-4287	-12663
Log-likelihood	-12035	-12067	-8101	-3923	-12068
Number of clusters	5549	5549	3747	1802	5549

p-value: *** p<0.001, ** p<0.01, * p<0.05. Robust standard errors in parentheses. Standard errors are clustered at the municipality level.

Figures

Figure A.1 – Pre-trends for % of Non-Standard Employment Relationships after a Coarsened Exact Matching on 2019 and 2020 NSERs

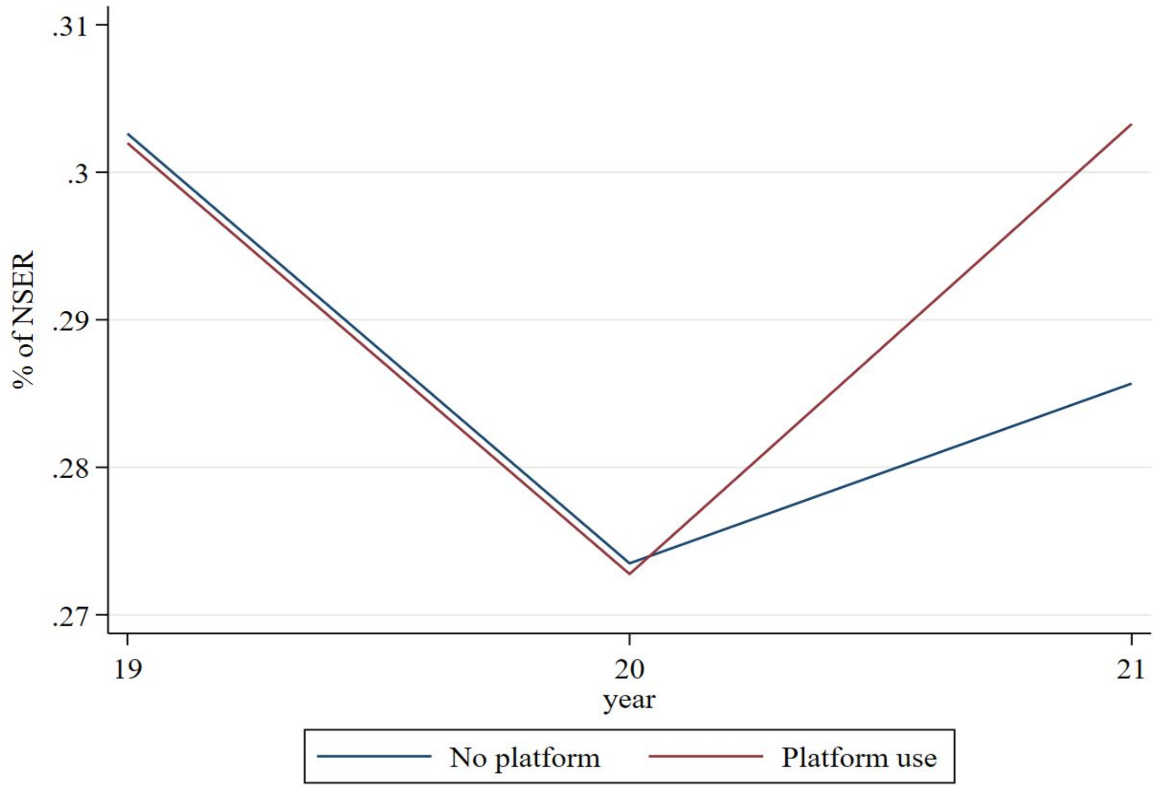

Figure A.2 – Marginal prediction for the share of NSERs in platform and non-platform firms – CEM estimates

Figure A.3 – Marginal prediction for the of NSERs in platform and non-platform firms – 2019 estimates

Digital Platform Survey: main items used for the measure

Digital platform use

C.01: Select one among the following: "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.)".

C.03b If you answered a) or b) to C.01, then “Is the third-party you mentioned using as digital sales channel a digital platform for intermediation? As digital platforms we mean an economic operator, identifiable as a website or an application, making online market intermediation between businesses and customers possible following the payment of commissions or fees on amounts paid (such as Airbnb, Deliveroo, Booking, Macingo).” Answers: 1) Yes, it is a digital platform for intermediation; 2) No, it is another digital instrument not resulting in intermediation.

Multihoming and platform dominance

C.05: Only for firms using digital platforms (answer 1 to C.03b): Referring to years 2020 and 2021, can you specify for each year the name of the platform(s) with which you had a contract? Specify first the most relevant platform in terms of your firm’s turnover (at most 3 platforms per year).

2020	2021
1°______________________________ __	1°______________________________ __
2°______________________________ __	2°______________________________ __
3°______________________________ __	3°______________________________ __

Platform-specific investment

C.12 To make use of the platform’s services did you have to make specific investments in goods or services (ex. IT equipment, specialized software, channel management services, advertising) ? 1) Yes 2) No, they would be necessary but I still did not make them 3) No, they are not required.