Segmentation of Working Time in the Gig Economy—A Panel Data Study[1]

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ABSTRACT

The re-organization of work via digital labor platforms has introduced fully flexible work schedules in courier services such as food delivery. However, little is known about how working activity on such platforms may vary over time. This study examines the working time patterns of a full population of food delivery workers in Denmark (N = 17,641) at the food delivery platform Wolt over 6 years (2017–2022). It identifies three worker segments: Dabblers *(few hours and short part-time over a few months),* Temporaries *(part-time for around 6 months), and* Regulars *(long part-time and full-time for 1-2 years). The results show that despite being a numerically smaller segment, Regulars increasingly perform the largest share of working hours. The article discusses implications of diversified working time patterns and uneven workloads across the three segments.*

KEYWORDS

digitalization / gig economy / labor market segmentation / Nordic labor market model / panel data / sequence analysis / working time flexibility

1. Introduction

Historically, the introduction of new work organizations and technology has led to a flexibilization of working hours across private and public sector workplaces (Haipeter 2020; Marginson & Sisson 2006). Over the last decades, the digitalization of work has refocused attention on working time flexibility, including its ties to business innovation and shifting working patterns at the societal level (Ó Riain &

[1] You can find this text and its DOI at https://tidsskrift.dk/njwls/index.

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Healy 2024). Digital labor platforms are often highlighted among the most far-reaching examples of these trends, as they pair algorithmically mediated task transactions with loosely defined self-employment arrangements that lack standard employment protections (Möhlmann et al. 2021; Vallas & Schor 2020). This is especially pronounced on so-called 'click work' (e.g., online product testing) and 'gig work' platforms (e.g., cleaning or courier services) that facilitate tasks of shorter duration and piece rate earnings with low skill requirements (Kalleberg & Dunn 2016). In the Nordic countries, these developments intersect with strong labor market institutions based on collective bargaining, where platform-mediated self-employment typically falls outside established regulatory frameworks (Oppegaard et al. 2025).

In recent years, a growing body of empirical work has focused on working time and other types of working conditions such as earnings, often in combination with demographic characteristics (e.g., age and nationality) (Kristiansen et al. 2022; Schor et al. 2020; Urzì Brancati et al. 2020; van Doorn et al. 2022). A key focus in these studies has been to explore how workers use these platforms differently—for example, for short-term or full-time employment—to understand which segments of the labor market engage with platform work (Urzì Brancati et al. 2020; Grimshaw et al. 2017). While much of this literature has relied on cross-sectional or self-reported data providing snapshots of working conditions, an increasing number of studies have started to analyze data from the platforms to trace how the flow of transactional activity actually unfolds within these flexible types of work organizations (Chen et al. 2019; Cullen & Farronato 2021; Piasna & Drahokoupil 2021). However, although existing research has documented fluctuations in working activity (Chen et al. 2019; Urzì Brancati et al. 2020), research has not yet clarified the extent to which platforms rely on short-term, part-time, and full-time workers, which has implications for how to approach regulation of these types of labor market (Oppegaard et al. 2025). Thus, longitudinal population data (i.e., panel data) appears particularly suited to addressing this empirical gap, as it enables the tracking of individual working patterns and shifts in workforce composition over time (Abbott 1995; Heckman & Singer 2008). This article addresses this empirical gap by analyzing working time series on a gig work platform through a two-fold research question:

What developments do we observe in individual working time trajectories on a gig work platform? What processes of segmentation unfold on this type of platform?

Our analysis focuses on a full-population panel dataset from Wolt, a large food delivery platform operating in Denmark. The data consist of individual working time series on all active couriers on the platform during 2017–2022 (N = 17,641), supplemented with demographic characteristics. To answer our research question, we use an analytical framework that combines the segmented labor market (SLM) approach with sequence analysis (Abbott 1995; Grimshaw et al. 2017). The SLM approach provides a useful lens for analyzing labor market divisions by treating working time as a critical indicator of segmentation, reflecting different levels of engagement and platform attachment (Doeringer & Piore 1971; Grimshaw et al. et al. 2017; Peck 1989). Further, sequence analysis enables us to categorize large volumes of longitudinal observations into patterned trajectories, which allows us to construct working time segments (Abbott & Tsay 2000).

The article makes two contributions. First, we identify three distinct working time segments—Dabblers, Temporaries, and Regulars—whose working time patterns vary in number of weekly hours and time spent (e.g., number of weeks) on the platform, ranging from sporadic short-term engagement to persistent long-term activity. Our analysis reveals variations in each segment's size and relative workload over time, with implications for the broader literature on platform labor and the Nordic context (Oppegaard et al. 2025; Urzì Brancati et al. 2020). Second, despite our dataset's limited variables, our longitudinal design demonstrates how time-based segmentation can be uncovered in flexible work settings. This approach may inform future studies of platform labor in similarly dynamic and less regulated contexts.

In the following, we develop our analytical framework drawing on the SLM approach, which we situate within the existing literature on platform work and Nordic labor markets. We then present our data and methodology. Next, we analyze our results, including the three identified working time segments and key developments over time. We conclude by discussing the implications and limitations of our results.

2. Analytical framework

2.1. Segmented labor markets and working time flexibility

We take our theoretical point of departure in the SLM approach, which provides a framework for analyzing working time in the gig economy. The SLM approach emerged as a structurally grounded response to dominant human capital-centered theories of labor market inequalities (Grimshaw et al. 2017; Rubery 2007). The SLM approach engages with how organizational and institutional conditions cause structural divisions and inequalities in employment conditions across industries and in the workforce (Rubery 2007). In the literature, a demand-side tradition underscores how employers perpetuate labor market inequalities by shaping working conditions such as wages and working time (Chung & and Tijdens 2013; Doeringer & Piore 1971; Eichhorst & Tobsch 2015). Additionally, a supply-side tradition addresses institutional factors outside the workplace, such as discriminatory policies or educational systems, and socio-economic aspects of the workforce, including gender, age, ethnicity, and educational background that restrict certain groups' access to job opportunities (Peck 1989; Seo 2021; Silberman et al. 2007).

Central to the SLM approach is the prevalence of dual labor markets, which are marked by workforces divided into distinct employment sectors with limited mobility (Doeringer & Piore 1971; Reich et al. 1973). As initially outlined by Doeringer and Piore (1971), the primary sector is dominated by so-called standard-employment with open-ended contracts, high wages, career progression, employment protection measures such as pensions, advancement and training opportunities, job discretion, and stable working hours. In contrast, the secondary sector comprises atypical employment arrangements characterized by temporary contracts with low pay without progression or overtime, limited social protection, and unsocial working hours (Doeringer and Piore 1971).

Particularly relevant to our focus on working time, the SLM literature has examined the flexibilization of working time and the 'diversification of working time patterns' (Campbell 2017:108) in contemporary labor markets (Rubery et al. 2016). The SLM literature considers working time flexibility to be more or less employer oriented (i.e., demand) or employee oriented (supply) (Chung & Tijdens 2013): While flexibility in the primarysector serves to attract or retain skilled workers (e.g., part-time options or phased retirements), in the secondary sector, it primarily serves employer interest in managing numerical flexibility and reducing labor costs—typically resulting in unpredictable, fluctuating (i.e., number of daily hours or weekly shifts), and unsocial working hours during evenings and weekends (Benassi & Kornelakis 2020; Rubery et al. 2016). These arrangements are prominent in gig work, typically situated within labor-intensive and volatile service industries such as cleaning, retail, hotels, and transportation (Kalleberg & Dunn 2016; Piasna 2020).

Gig platforms represent an extreme case of employer-oriented flexibility by operating with self-employed working arrangements facilitated through a digitalized organizational structure (Vallas & Schor 2020). Apart from self-employment, the most debated aspect of gig work concerns these platforms' use of algorithmic management systems to allocate shifts and calculate earnings based on real-time demand, thus replacing traditional managerial oversight with data-driven principles (Möhlmann et al. 2021; Stark & Pais 2021). As such, while employment contract details (e.g., the number of working hours stated in the contract) have traditionally been used in the SLM approach as a central indicator for segmentation, the platforms' tendency to avoid formal employment contracts necessitates a different way of operationalizing the SLM approach (Grimshaw et al. 2017): Since gig work is task-based and workers can log in and stay active on the platforms without limitations (Vallas & Schor 2020), the most significant differentiator between workers is their actual number of working hours. Adapting the SLM approach to encompass an actual working hours differentiator allows us to explore segmentation through the workers' temporal patterns of work activity, revealing their varying attachment and engagement with the platform (Campbell 2017). Further, consistent with the SLM tradition, we consider gig workers as possessing typical secondary-sector characteristics—including being self-employed and performing low-skilled, easily replaceable tasks (Doeringer & Piore 1971; Kalleberg & Dunn 2016). Accordingly, more secure in-house platform positions for employees such as developers or designers are excluded from our analysis.

2.2. Segmentation in the gig economy

Our analytical framework relates to a growing body of empirical work that demonstrates segmentation within various digital labor markets. As noted in the platform literature, and in line with secondary labor market characteristics (Campbell 2017), platform work offers low-barrier access to temporary work for a wide range of different workers, but is also marked by precarity due to the loosely defined working conditions (Schor et al. 2020). Qualitative studies have shown that gig work disproportionately attracts workers in marginalized positions, such as migrants and others with limited access to stable employment (Heiland 2022; van Doorn et al. 2022). The availability of large pools of such workers provides platforms with a steady inflow of labor, compensating for high turnover and low worker commitment caused by the insecure employment conditions (van Doorn et al. 2022:1101). A number of survey-based studies have further demonstrated how segmentation in platform work aligns with demographic characteristics such as gender, nationality, and education level, as well as differences in working time, earnings, and reliance on platform income (Kristiansen et al. 2022; Piasna et al. 2022; Urzì Brancati et al. 2020). These studies reveal an overrepresentation of foreigners and students, and gender imbalance among workers who engage with platforms at varying levels of intensity and income dependence (Kristiansen et al. 2022:66; Piasna et al. 2022:29; Urzì Brancati et al. 2020:21). In addition to the studies using cross-sectional data such as interviews and surveys, an increasing number of studies based on platform-generated data have explored how segmentation manifests in real-time activity, including working hours, earnings, and responsiveness to platform demand (Chen et al. 2019; Cullen & Farronato 2021; Piasna & Drahokoupil 2021).

Key studies examining working time and segmentation include Urzì Brancati et al.'s (2020) survey-based categorization of platform workers in Europe that divides workers into three distinct groups of (1) marginal (< 10 weekly hours, 25% of total income), (2) secondary (10–19 weekly hours, 25–50% of total income), and (3) main (> 20 hours and > 50% of total income) platform workers (Urzi Brancati et al.:15). Further, Chen et al.'s (2019) analysis of the working time and earnings of a large dataset of Uber taxi drivers in the United States found a large majority of workers working limited hours and part-time (82%), and a smaller proportion working full-time (18%). We discuss these findings on working time segmentation in relation to the results of our analysis.

2.3. Gig work in the Nordics

We situate our analytical framework within discussions of platform work in the Nordic labor markets. While the proportion of workers engaged in platform work remains relatively small—estimated at 1–2% in Denmark, 1% in Finland, 2% in Sweden, and 2–4% across the European Union (Ilsøe & Larsen 2021; Piasna et al. 2022; Sutela & Pärnänen 2018)—platform work reflects broader trends toward non-standard, under-regulated employment that increasingly challenge the institutions of the Nordic labor market model (Rasmussen et al. 2021). Denmark, our empirical setting, is characterized by a voluntarist labor market model with minimal state intervention and high collective bargaining coverage (Rasmussen et al. 2021). Approximately 80% of Danish employees are covered by collective agreements, and trade union density stands at around 65% (Arnholtz & Navrbjerg 2020). The system is supported by a relatively generous social security net, though access is more limited for foreigners and particularly for non-EU nationals (Bredgaard & Madsen 2018). While collective agreements regulate wages, working hours, and social protections (e.g., pensions), they have historically focused on standard full-time employment. However, the last two decades have seen a sharp rise in non-standard work arrangements—including marginal part-time employment (under 15 hours per week), zero-hour contracts, and solo self-employment (Rasmussen et al. 2021). As of 2019, these forms of work comprised roughly one-third of the Danish workforce (Rasmussen et al. 2021). The arrival of gig work platforms in the mid-2010s, operating outside the normal scope of the Nordic labor market models and regulation, reflects these trends and tests the viability of the models (Oppegaard et al. 2025).

Oppegaard et al.'s (2025) comparative analysis of platform companies' trajectories in Nordic labor markets identifies a trend showing that many platforms position themselves outside traditional regulatory structures by classifying workers as self-employed while attracting marginalized segments of the workforce such as migrants with limited alternatives. This development has provoked significant public and political criticism, including the platforms' extensive use of algorithmic management practices—and has spurred a range of responses—from platform exits to efforts aimed at forming new types of collective agreements (Oppegaard et al. 2025). In some cases, so-called 'hybrid models' (Jesnes 2019) have emerged in Norway, Sweden, and Denmark, suggesting a 'Nordic platform model' (Ilsøe & Söderqvist 2023). This arrangement seeks to combine working time flexibility with varying basic protective measures such as minimum hourly wage floors, guaranteed working hours, social protections (pensions, paid holiday, and sick leave), algorithmic transparency and unionization rights (Ilsøe 2025; Oppegaard et al. 2025). However, attempts at developing hybrid models have sometimes faltered, as in the case of Wolt, where Wolt's negotiations with the Danish trade union 3F collapsed when Wolt refused to accept an existing sector level agreement that included minimum weekly working time standards, an agreement which Wolt's competitor Just Eat had already joined (Marenco 2024). Platform managers in Denmark and Finland (including Wolt's management) report a 'coming and going' culture (Haldrup et al. 2024) at their platforms, and justify their refusal to join collective agreements by claiming the agreements are too rigid and misaligned with the flexible working time preferences of today's workforce (Immonen 2024). Thus, working time flexibility remains central to conflicts over regulation of gig work in the Nordics.

3. Data and methodology

3.1. Longitudinal platform data

The data for this study were provided by the gig work platform Wolt. While we requested numerous variables for analyzing gig work longitudinally at different levels of detail (e.g., hourly individual earnings and working hours distribution during the day), the platform agreed to provide us with working time data in the form of the couriers' summarized online hours on a weekly basis. Wolt entered the Danish labor market in 2017, and facilitates food and grocery delivery across Danish towns and cities. Wolt also operates in the other Nordic countries and several other countries (Oppegaard et al. 2025). The platform's app design connects customers, restaurants, supermarkets, and 'courier partners' (i.e., the self-employed freelancers, who are represented in our summarized online hours data). Table 1 summarizes the key characteristics of the data.

Table 1 Overview of data

Source	Population	Sample size (N)	Level of analysis	Indicator (longitudinal)	Period
Company registers	Food delivery couriers	17,641	Individual trajectories	Weekly online hours	2017–2022

As seen in Table 1, the dataset contains individual-level activity data of all food delivery couriers who worked for Wolt in Denmark between February 2017, where the platform started operating in Denmark, and until the last week of 2022. Although the full dataset includes 20,090 individual courier trajectories, we excluded those that began in the second half of 2022. We assessed that the limited duration of these trajectories, possibly continuing into 2023, would not permit meaningful longitudinal analysis and risked misclassification due to their limited recorded activity. This left us with a sample size for analysis of 17,641 couriers, whom we analyze by weekly online hours.

The online hours appear as a continuous variable in the dataset and include the total hours per week couriers were logged onto the platform app (values between 0 and 126 hours). Therefore, the variable not only captures working time activity when couriers deliver orders but also other types of activity when couriers are logged onto the app, such as waiting for incoming or delayed restaurant orders (Pulignano et al. 2023). As such, the data allow us to analyze weekly working time fluctuations and trace developments across 6 years from a full population of gig workers during the studied period.

3.2. Demographics

In the dataset, each courier has a unique ID number, encrypted for GDPR compliance. This encryption prevented us from linking the data to individual background data on the couriers in national registers. Instead, the platform provided us with the couriers' self-reported (but optional) information about key demographics, including gender, age, nationality, and VAT registration. Due to inconsistent data monitoring by the platform and resulting high proportions of missing values in the self-reported data—especially among couriers with short-term activity on the platform—we omitted most of these self-reported variables from the analysis, with an exception of nationality and tax registration form. The nationality variable allows us to relate our results to the existing literature on segmentation that shows that foreign workers, particularly non-EU workers, face discriminatory and legislative barriers to employment and to welfare services (Bredgaard & Madsen 2018; Silberman et al. 2007; van Doorn et al. 2022). Further, the couriers' type of tax registration indicates whether couriers register earnings with the tax authorities as personal income [using their civil registration number (CPR)] or as income in a registered sole proprietorship [using their VAT registration number (CVR)]. In Denmark, VAT registration is required for self-employed individuals earning more than €6600 annually and enables them to make expense deductions in tax returns, take out insurance in an unemployment insurance fund, and draw on publicly funded benefits such as maternity leave benefit and sickness leave benefits (Larsen & Mailand 2018).

3.3. Reliability

Using data provided by a platform company entails certain methodological risks (Lazer et al. 2021). For instance, a study using Uber data in the United States faced criticism for lack of transparency in the data provided by the platform (Berg & Johnston 2019). To address this potential issue, we established a Non-Disclosure Agreement (NDA) before the data exchange, which was verified by the legal departments of Wolt and the University of Copenhagen (UCPH). The Tech Transfer Office at UCPH drafted the NDA, and comments were received from Wolt and all participating researchers. The NDA specifies data exchange conditions, including accessibility and research independence. We specified our data requirements (i.e., individual level, online hours, and demographics) within the NDA. Our initial analysis of the data indicated that the platform had delivered the data in a raw format that was not edited to align with company policies (Lazer et al. 2021).

For instance, the working time series includes numerous instances of individual couriers exceeding 100 weekly online hours, potentially because some couriers remain logged onto the platform even after concluding their work, or because several couriers may share a profile. We regard courier activity indicating unusually high workloads as contradicting a platform company's interest in promoting themselves through offering the prospect of flexible working time rather than labor-intensive full-time work (Immonen 2024; Marenco 2024). As such, this increases the likelihood that the platform did not alter the working time data before the data transfer.

3.4. Analytical strategy: Sequence analysis

To analyze working time segmentation on the platform, we employed sequence analysis, which was originally conceptualized by Abbott (1995) as a process-oriented and descriptive approach for understanding temporary patterns of social activity. Sequence analysis has been widely used to systematically analyze different types of life course trajectories such as employment stability (e.g., job changes over time) among individuals engaged in non-standard work (Abbott & Tsay 2000; Berglund et al. 2023; Ojala et al. 2018), but until now, not in studies of gig work.

We used sequence analysis to examine the 6 years of longitudinal observations in our data set (2017–2022) to identify trends and developments in the 17,641 working time trajectories (Abbott 1995). Further, we enhanced this micro-level analysis with clustering methods in R to pool similar sequences and construct segments based on working time variation, from which we produced descriptive statistics (Abbott & Tsay 2000).

Our clustering process for working time sequences involved three analytical steps with the R package TraMineR, a programing tool developed for sequence analysis (Gabadinho et al. 2011). The steps included (1) coding of the working time data into sequence categories, (2) establishing a statistical measure for clustering sequences with similar patterns of activity, and (3) choosing the appropriate number of sequence clusters for analysis.

First, as illustrated in Table 2, we coded the continuous 'online hours' variable into six working time states (i.e., categories) to construct sequences out of the courier trajectories for a systematic comparison of working time activity.

Table 2 Working time states (weekly online hours) in courier trajectories

Working time states	Full-time	Long part-time	Short part-time	Few hours	Inactive	Not on platform
Weekly online hours	+30	15–30	5–15	<5	0	–

The working time states were partly inspired by categories in previous research (Piasna et al. 2022; Urzì Brancati et al. 2020), including 'Full-time', 'Long part-time', and 'Short part-time' and 'Few hours'. We also included an 'Inactive' category, which captures weeks where couriers were on the platform but logged minimal activity (i.e., less than 2 hours). Finally, the 'Not on platform' state refers to weeks when couriers were not present on the platform.

Second, to systematically cluster the working time sequences, we initially assessed the consistency of working time patterns across all 17,641 sequences (see transition probabilities in Table A1, appendix). This revealed relatively high probabilities of couriers remaining within the same type of working time activity rather than fluctuating randomly between the six working time states. For instance, a courier working part-time on the platform would be likely to work short part-time on a weekly basis or, alternatively, transition to a neighboring state (e.g., long-part-time). We therefore applied a statistical measure for systematically clustering sequences with minimal dissimilarities or 'substitution costs', which refers to the least number of actions to 'turn one sequence into the other' (Lesnard, 2010:391). Specifically, we applied the 'optimal matching' (OM) method to account for the rather stable working time patterns in the sequences, reflecting low substitution costs for matching similar working time states and high costs for matching very different states (see substitution cost matrix in Table A2, appendix). To provide an example, Table 3 illustrates three types of working time sequences in the data.

Table 3 Example of three working time sequences

Week	1	2	3	4	5	6	7	8	9	10
Courier A	0	<5	5–15	<5	<5	0	–	–	–	–
Courier B	<5	<5	5–15	15–30	5–15	5–15	5–15	5–15	<5	<5
Courier C	5–15	15–30	15–30	+30	+30	+30	+30	+30	+30	+30

In Table 3, the cost of substituting 'few hours' (<5) with 'full-time' (+30 hours) between courier A and C in week 4 is higher than the cost of substituting 'full-time' with the neighboring state of 'long part-time' (15–30) for courier B in week 4.

Third, we conducted tests to empirically and theoretically determine the appropriate number of clusters for our analysis. Empirically, this included evaluating different clustering solutions based on 'Ward's method' according to (1) the consistency of clusters, (2) the best theoretically possible clustering of the data, and (3) OM for substituting working time states (Landau & Chis Ster 2010). We also ran the tests in individual calendar years (2017, 2018, etc.) to account for variations in platform activity over time. The tests revealed that two clusters would lead to a high proportion of asymmetric sequences within clusters, while four or more clusters would lead to very subtle differences between clusters—such as two separate clusters containing similar low-activity patterns. We therefore chose a model with three clusters to illustrate three distinct segments of gig workers based on their varying working time activity.

4. Results: Three working time segments

The following figures and tables present our main findings on three distinct working time segments. First, we describe the typical working time patterns of each segment. Second, we complement these results by demonstrating how these segments have evolved between 2017 and 2022.

Figures 1–3 display sequence outputs of the working time patterns of couriers in each of the three segments over time. For a clearer comparison and visual illustration of the working time patterns in the segments, all couriers' starting weeks (week 0) have been aligned in these sequences regardless of when they joined the platform. The y-axis displays the proportion of couriers in different working time states in a given week, while the x-axis plots this distribution over time. The different colors represent the six working time states—for example, the green color indicates full-time work, while the pink color reflects when couriers stop using the platform.

Figure 1 Distribution of weekly activity (segment 1).

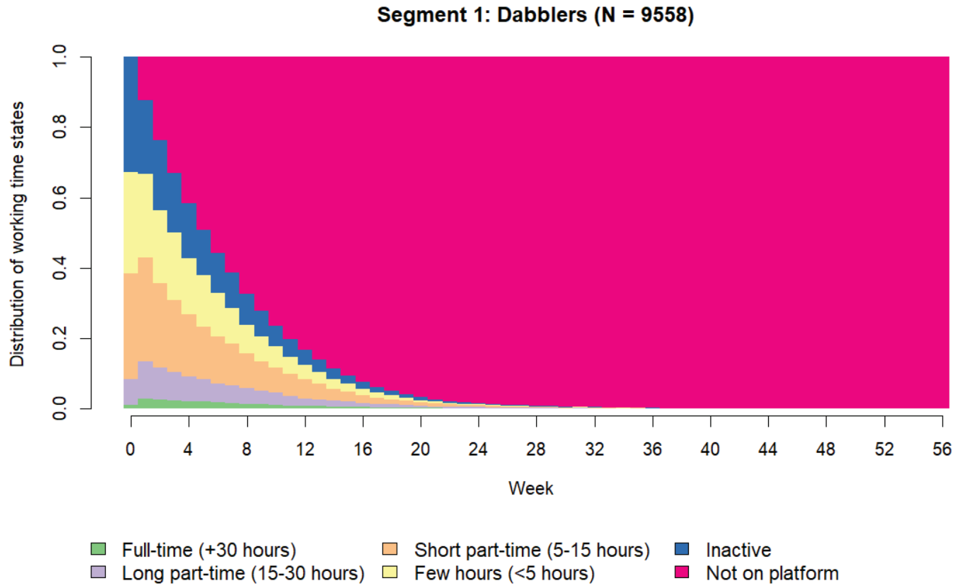


Figure 2 Distribution of weekly activity (segment 2).

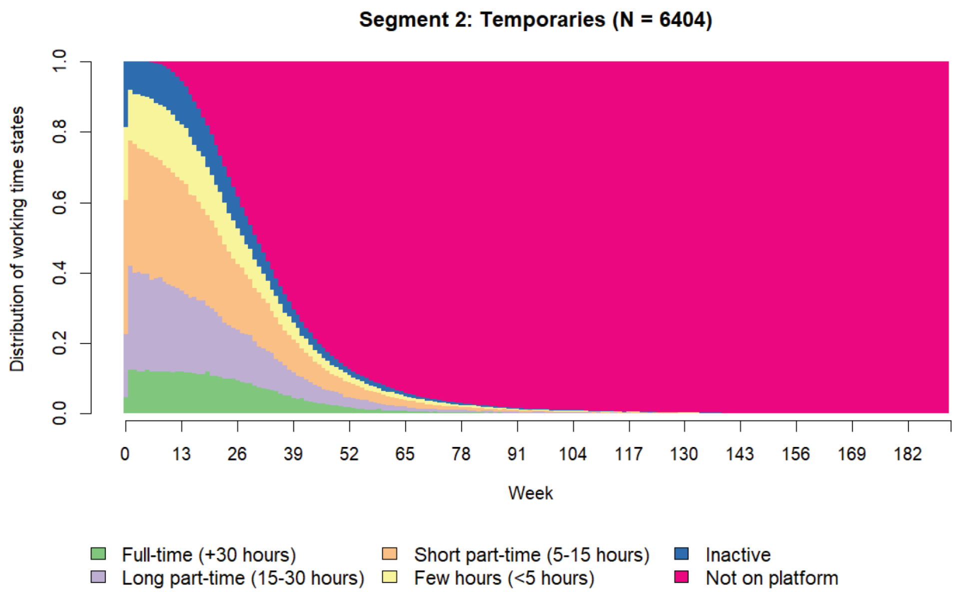
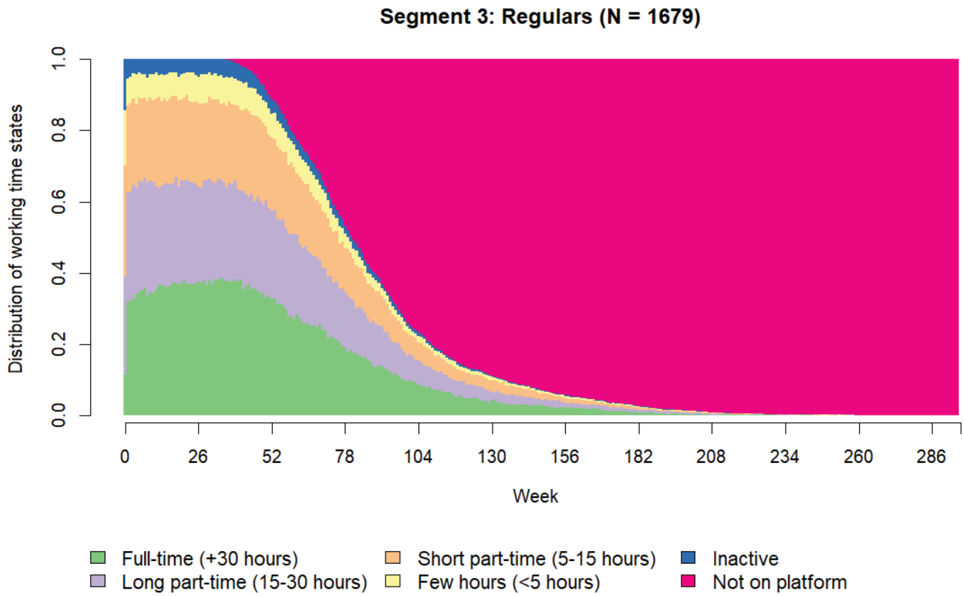


Figure 3 Distribution of weekly activity (segment 3).



In the three figures, each of the names allocated to each of the segments—Dabblers, Temporaries, and Regulars—reflect distinct patterns of working time activity.

(1) Dabblers (Figure 1). This segment demonstrates limited activity on the platform and is the largest, comprising 9558 couriers. When active, they most often work short part-time hours (5-15), followed by few hours (<5) and frequent inactivity. On average, Dabblers have 9 hours of activity per week. Their engagement tends to be brief, with an average sequence length of only 7 weeks, indicating that most leave the platform a few months after joining.

(2) Temporaries (Figure 2). This segment includes 6404 couriers with moderate platform engagement. Temporaries primarily work part-time hours, both short (5-15 hours) and long (15-30 hours), averaging 15.4 online hours per week. Compared to Dabblers, Temporaries typically remain active for a longer period—with an average sequence length of 35 weeks—suggesting engagement lasting around half a year.

(3) Regulars (Figure 3). Regulars are the most active and consistent on the platform, though they form the smallest segment with 1679 couriers. They are mainly engaged in long part-time (15–30 hours) and full-time (+30 hours) work. Regulars average 24.2 hours per week and stay on the platform for longer terms, reflected in an average sequence length of 88 weeks—approximately 1.5 years.

4.1. Longitudinal trends of the three segments

Despite the distinct working time characteristics of each segment, their relative presence on the platform changes when analyzing their activity during the 6 years. As illustrated in the following two figures, these developments relate to an increase of online hours and the number of active couriers, where part-time and full-time activity becomes increasingly present among couriers on the platform.

Figure 4 The three segment's share of weekly online hours over time (February 2017–June 2022).

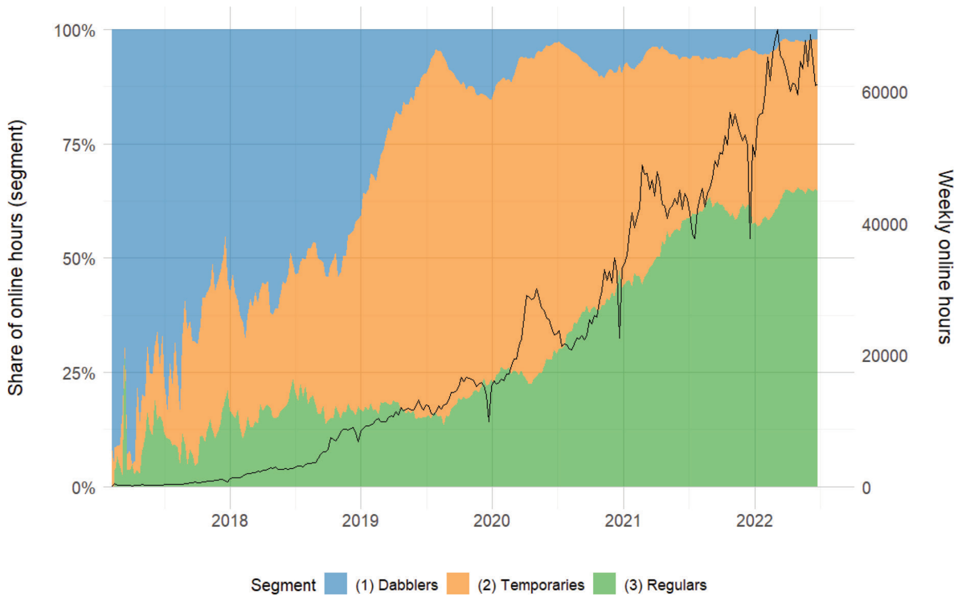
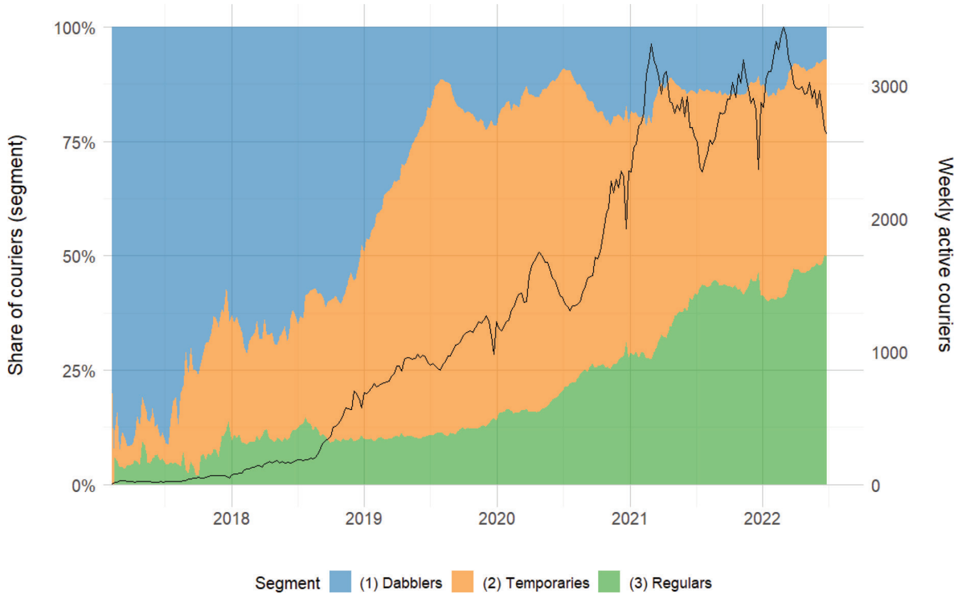


Figure 4 shows the segments' shares of the total weekly online hours on the left y-axis, with the total weekly online hours (black line) on the right y-axis. In the first 2 years, the platform activity is driven mainly by Dabblers' short-term activity, which account for the majority—more than 50%—of the comparably low (less than 10,000) weekly number of online hours. A notable trend in Figure 4 is the sharp increase in online hours from 2020 onwards with weekly online hours tripling from ~20,000 to more than 60,000 weekly hours by 2022—despite some seasonal drops during the middle and at the end of each year. The development is primarily driven by Temporaries in 2019 and 2020, which is followed by Regulars, where the large increase in activity from 2021 is characterized by the full-time activity of Regulars starting to dominate the platform, making up around 60% of the total weekly online hours in 2022.

Figure 5 shows similar comparable developments in the number of active couriers on the platform and each segments' share of couriers over time—although the number of weekly active couriers appear to stabilize around 3000 from 2021 onwards. In this period, Regulars' presence increases significantly, comprising nearly half of all the couriers on the platform during 2022 at the expense of the two other segments. This increase in Regulars' presence in the total number of couriers and online hours (Figure 4) on the platform coincides with an increase in Regulars' average weekly number of online hours—from 20 weekly hours in early 2020 to 30 weekly hours in 2022. In comparison, the average weekly hours remain stable for Dabblers and Temporaries, despite their varying share of couriers between 2017 and 2022.

Figure 5 The three segment's share of couriers over time (February 2017–June 2022).



4.2. Summarized characteristics and demographics

The varying size and working time activity of the segments over time reveal key differences in workloads across courier segments. Table 4 summarizes each segment's share of the total number of couriers (N = 17,641) and the total number of online hours logged across the 6 years on the platform.

Table 4 Summarized characteristics of the three segments (2017–2022)

	Share of total online hours*	Share of couriers*
1. Dabblers	7.1%	54.2%
2. Temporaries	42.3%	36.3%
3. Regulars	50.7%	9.5%

Table 4 reveals a notable reciprocal relationship between courier share and online hours for Dabblers and Regulars: although Dabblers represent more than half of all couriers (54.2%) between 2017 and 2022, their short-term activity and few weekly hours contribute with only 7.1% of total online hours. Conversely, despite being numerously small, couriers in the Regulars segment account for half (50.7%) of the working time activity on the platform. Between these two segments, Temporaries occupy a middle ground in terms of size, while also accounting for a large share (42.3%) of the total online hours.

While the working time data reveal clear trends of platform segmentation, our prospects for connecting these insights with socioeconomic characteristics are limited by the low quality of our demographic data. Therefore, Table 5 provides only the nationality and tax registration type of the Regulars. Missing values comprising around 60% for Dabblers and 30% for Temporaries render these data insufficient for analysis.

Table 5 Nationality and tax registration type of Regulars 2017–2022

	Nationality*		**Tax registration***	
Regulars	Denmark	20.1%	Personal income	21.0%
	EU/ESS	40.5%	VAT registered	78.7%
	Third country	38.4%		

N = 1449. *Missing values: 1% (nationality) and 0.3% (tax registration).

Table 5 groups couriers' nationality into three categories: Denmark, EU/EEA, and third countries outside the EU/ESS, based on the literature suggesting foreigners face discriminatory challenges on the labor market (Bredgaard & Madsen 2018; Silberman et al. 2007). As Table 5 shows, a large majority (79.9%) of Regulars have a foreign background. The tax registration type indicates whether couriers report earnings with the tax authorities as personal income [using their civil registration number (CPR)] or as income in a registered sole proprietorship [using their VAT registration number (CVR)]. A large proportion (78.7%) of Regulars are VAT registered, allowing them to deduct expenses in their tax returns and access certain publicly funded labor market schemes (Larsen & Mailand 2018).

5. Discussion and conclusions

Our identification of three distinct working time segments Dabblers (limited short-term activity), Temporaries (part-time activity for around 6 months), and Regulars (full-time activity for 1-2 years) both resembles and expands existing models of segmentation from existing literature. The segments align with the categorization by Urzi Brancati et al. (2020) of platform workers into 'sporadic/marginal' (<10 hours), 'secondary' (10-20 hours), and 'main' (+20 hours). This suggests that these working time segments appear both across different types of platforms and within specific gig work contexts. Further, consistent with previous research based on gig work platform data (e.g., Chen et al. 2019), our results show that part-time work is widespread in these types of working arrangements, and full-time work less prevalent. The majority of couriers (90.5%) fall into the Dabbler and Temporary segments, while Regulars constitute 9.5%, compared to 82% and 18%, respectively, in Chen et al. (2019). While these other studies contain a much richer range of variables than our study (including earnings), they rely on reported data based on larger workforce samples (Urzì Brancati et al. 2020) and a limited time-span of activity data (Chen et al. 2019). Our longitudinal analysis of a working time data series over 6 years reveals not only these three working time segments but also their evolving presence over time.

Perhaps the most notable contribution of our analysis concerns the emergence and growth of full-time work, represented by the increasing presence of Regulars. Despite this platform representing an extreme case of algorithmically managed, task-based work organization (Vallas & Schor 2020) designed to allow both minimal and sustained engagement, the Regulars' full-time activity accounts for a significant part of the increasing workload conducted on the platform from 2017 to 2022. Between 2020 and 2022, the number of online hours tripled on the platform, and by 2022, Regulars accounted for 60% of all online hours. While this growth coincides with broader trends in the expansion of food delivery platforms—particularly during the COVID-19 pandemic (Cullen & Farronato 2021; Rani & Dhir 2020), it also indicates a demand-driven trend that supports sustained, full-time engagement (Campbell 2017).

5.1. Regulatory implications

These results raise important questions about how platforms establish themselves on different labor markets and how regulatory initiatives can accommodate diverse forms of platform engagement. In the Nordic context, some platforms have adopted 'hybrid models' (Jesnes 2019) to gain legitimacy by aligning themselves with collective bargaining traditions to balance flexibility with protective measures (Oppegaard et al. 2025). In contrast, the platform analyzed in this article has upheld its self-employment model by arguing that existing collective agreements are incompatible with workers' flexibility needs (Immonnen 2025; Marenco 2024). A recently adopted EU Directive on Platform Work introduces a presumption of employment, which may compel platforms to reclassify workers as employees unless they can prove genuine self-employment (European Parliament 2024). While the implementation and legal consequences of this directive remain uncertain, it could significantly impact platforms that currently avoid collective agreements, such as the one examined here.

Our results challenge these platforms' continued justification of self-employment. While the alleged 'coming and going' culture (Haldrup et al. 2024) may have accurately described Wolt's early phase in the Danish labor market (2017-2019), by 2022, the platform increasingly relied on a small but stable group of full-time couriers to meet its labor demands. Demographically, 80% of Regulars have a foreign background, echoing findings that platforms tend to attract migrant workers in precarious labor market positions (Oppegaard 2025; van Doorn et al. 2022). These workers are not the most numerous, but they carry out a disproportionately high share of the total workload. Although many Regulars are VAT registered (78.8%), a 2023 ruling by the Danish Tax Authority classifies couriers as employees for tax purposes, requiring the platform to handle tax reporting of couriers' income from the platform (Oppegaard et al. 2025). This ruling has weakened the practical advantages of self-employment, as it no longer allows couriers to deduct expenses, while the remaining dimensions of their working conditions bear the individualized risk of self-employment (Oppegaard et al. 2025).

Our results therefore support the need for establishing protective measures in line with recent Nordic developments (Ilsøe & Söderqvist 2023; Jesnes 2019) that take diversified working time patterns into account. Such initiatives should also include measures to address the potential health and safety implications of physical and mental wear stemming from full-time platform work (Williams et al. 2022).

5.2. Limitations and future studies

While this article offers a rare opportunity to examine gig work dynamics longitudinally, several limitations should be acknowledged. These limitations offer directions for future research that may draw on the longitudinal research design of this article to inform ongoing debates around digital labor markets.

First, one important limitation of the working time series in the dataset relates to platform policies that automatically delete user accounts inactive for several months (Lazer et al. 2021), which made us unable to trace workers leaving and reentering the platform over longer periods.

Second, and most importantly, the studied data only contain a single dependent longitudinal indicator (i.e., online hours) and low-quality demographics. This limits our ability to engage with important questions about socioeconomic stratification on gig platforms and related workplaces – for instance whether the large share of Regulars with foreign backgrounds belong to marginalized segments of the workforce with limited labor market opportunities (Oppegaard et al. 2025; van Doorn et al. 2022). Future studies should seek to integrate demographic data with longitudinal working time activity, including earnings, to better understand how supply-side (e.g., access to alternative employment) and demand-side mechanisms (e.g., platform demands) jointly shape labor force segmentation over time (Grimshaw et al. 2017). This would enable assessment of which worker segments benefit from temporal flexibility (Schor et al. 2020) – such as those optimizing for peak hours as indicated in Chen et al. (2019)—and which workers are forced to remain available during low-demand periods. Additionally, building sequences of broader employment trajectories that combine working activity (e.g., working hours) in both platform work and other types of jobs would offer insights into platform work as one way of engaging in multiple jobholding (Kristiansen et al. 2022). Connecting platform activity data with company-side demand indicators (Doeringer & Piore 1971), such as order volumes, would also enhance our understanding of how worker behavior adapts to platform demand and the seasonal variations evident in our results (Cui et al. 2022; Cullen & Farronato 2021).

Finally, the generalizability of our findings is constrained by the platform-specific nature of the data, as our platform represents a less restrictive algorithmic management regime allowing workers to accept and reject orders without facing potential penalties (Haldrup et al. 2024; Immonen 2024). Gig platforms differ substantially in how they structure algorithmic management (e.g., task allocation, remuneration) and working conditions (e.g., task- or shift-based systems), which influence worker autonomy (Pulignano et al. 2023). Additionally, institutional factors such as national labor market regulations also influence platform operations and their workforce composition (Grimshaw et al. 2017). Future studies should therefore investigate comparable longitudinal data across various platforms and national contexts.

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Appendix

Table A1 Transition probabilities (2017–2022)

	Full-time	Long part-time	Short part-time	Few hours	Inactive	Not on platform
Full-time	0.69	0.21	0.05	0.01	0.01	0.02
Long part-time	0.18	0.47	0.24	0.04	0.03	0.05
Short part-time	0.04	0.19	0.41	0.14	0.07	0.15
Few hours	0.01	0.06	0.26	0.21	0.12	0.34
Inactive	0.01	0.05	0.17	0.14	0.21	0.42
Not on platform	0.00	0.00	0.00	0.00	0.00	0.99

The table shows how likely a courier originating in one the six working time states (vertical cells) is to transition to the same or a different working time state (horizontal cells) (Gabadinho et al. 2011). For instance, a courier working 'Full-time' (+ 30 hours) has a very high probability (69%) of staying in Full-time the next week, and a very low probability (1%) of transitioning to 'Few hours' the next week.

Table A2 Substitution cost matrix based on transition probabilities (2017–2022)

	Full-time	Long part-time	Short part-time	Few hours	Inactive	Not on platform
Full-time	0.0	1.6	1.9	2.0	2.0	2.0
Long part-time	1.6	0.0	1.6	1.9	1.9	1.9
Short part-time	1.9	1.6	0.0	1.6	1.8	1.8
Few hours	2.0	1.9	1.6	0.0	1.7	1.7
Inactive	2.0	1.9	1.8	1.7	0.0	1.6
Not on platform	2.0	1.9	1.8	1.7	1.6	0.0

This matrix illustrates the cost of replacing one working time state (vertical cells) with another state (horizontal cells) as a part of our applied OM method for matching trajectories with minimal costs. The values are calculated from the transition probabilities from Table A2. For instance, the cost of replacing 'Full-time' with 'Full-time' is 0, while the cost of replacing 'Full-time' with 'Inactive' is 2.