“It’s like Uber,” but for deepening political inequality:

Estimating the impact of platform economy work on workers’ political interest and voter turnout in the UK

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Executive Summary

The platform economy has attracted an increasing amount of media attention over the past decade, particularly during the early months of the pandemic as lockdowns spurred demand for delivery and other common platform services. There does not seem to be one prevailing attitude on the platform economy: while some hail it as a new future of flexible work opportunities and on-demand services, others are concerned about exploitation of gig workers or platform companies crowding out traditional, local services. Further, as self-described “disruptors” of the labor market and service economy, many platform companies have ambiguous legal status, presenting tricky policy problems across labor, consumer protection, and taxation. While there have been recent efforts to study and then regulate the platform economy (for example in the EU), Liberal Market Economies (LMEs) like the US and the UK are hesitant to pursue serious regulation. This hesitation has serious implications for platform workers in particular, who often work for low wages, lack basic employment protections, and have limited future career prospects. Left unchecked, platform work risks marginalizing many platform workers within both the labor market and society in general.

This thesis attempts to assess one potential downstream effect of participating in platform work, one that has implications for social cohesion and healthy democracies: political interest and voter turnout. As rich democracies see declining voter turnout, and political inequalities deepen along socioeconomic lines, the platform economy has the potential to be a new driver of political inequality. To investigate this connection, I first use Probit regression modeling to predict selection into platform work across socio-demographic and financial/social insecurity variables. Then, incorporating findings from this first set of models, I model political interest and voter turnout on gig work, controlling for known predictors of political outcomes (education, gender, income, etc) and for various work and financial security variables. Further, I test the effects of different categories of gig work: manual vs non manual, reliant on vs casual.

First, I find that indeed, platform workers are not a monolithic group, but rather can be sorted into typologies which differ from each other in meaningful ways. Second, I find that these types of platform work see different effects on political interest and voter turnout: non manual workers on average have more political interest and vote more, whereas manual workers are less likely to vote, despite having similar levels of political interest as the general population. These effects are robust to multiple specifications and are partially supported by Propensity Score Matching, a non-parametric approach I use as a robustness check. These findings invite future research into political identities among platform workers, their policy preferences, and what to expect in terms of their future political action.

1. Introduction

The platform economy invites us to imagine a future where services are procurable anytime and anywhere, simply by downloading a smartphone app. Platform services can make us feel informed and in control, giving us access to crowd-sourced reviews, photos, and safety verifications while also inviting us to contribute to the "community" of app consumers by writing reviews ourselves. We are told that the workers providing these services are equally in control, allowed to set their own hours and even rate us as consumers (as with Uber and AirBnB). So why does the platform economy spark so much discomfort, even anger, for many?

It is in part because these promises of safe, flexible work opportunities seem to ring hollow. News coverage on platform workers—usually delivery or Uber drivers—nearly always highlights the grueling working conditions, the unfair labor practices, and the customer abuse many platform workers endure. Berlin's homegrown start-up Gorillas, a grocery delivery company, was in the media spotlight for much of 2021 as delivery riders organized strikes and protests over unpaid wages and insufficient gear (Flakin, 2021). The overall narrative speaks to platform workers existing on the margins, economically and even socially.

This thesis focuses on platform work's intersection with democracy: specifically, its intersection with voter turnout. Why? The quality of a democracy can be judged in part by the extent to which it involves, consults, and represents its citizens, and by many accounts, things are not going entirely well across rich democracies: voter turnout significantly declined over the latter half of the 20th century, first in the US and now in many European nations as well (Blais & Rubenson, 2012; Gray & Caul, 2000). Platform work, while a relatively new phenomenon, has potential as a new driver of political inequalities and suppressing voter turnout among platform workers. Much has been written about the connections between work and political mobilization, and recently there has been a small frenzy of research on platform work, but to my knowledge, no study has thus far attempted to measure quantitatively the impact of platform work on political outcomes. With this thesis, I hope to draw these two strands of research together. Using Probit regression modeling, I find that on average, platform workers in the UK are more likely to express political interest, but for some groups, they are also less likely to vote. In particular, manual gig workers are nearly 7 percentage points less likely to vote than non gig workers. Relatedly, I find significant heterogeneity among gig workers in terms of their characteristics and political behavior, but that this variation can be simplified into meaningful, predictive categories: manual vs non manual, and being reliant on gig work vs casual gig work. These findings are relevant both for labor market researchers studying the effects of the platform economy, as well as political economy researchers investigating drivers of declining voter turnout in rich democracies.

In Section 2, I will review some of the existing data and literature on platform work and theories of political mobilization, then present my research questions and hypotheses. Section 3 explains my methods and introduces the dataset, then Section 4 explores findings and robustness checks. Finally I will conclude with a brief discussion of findings (including a short reflection on policy implications), elaborate on the limitations of my study, and invite future research in Section 5, before coming to a conclusion in Section 6.

2. Platform Work and Political Engagement: a review of the existing data, theory, and literature

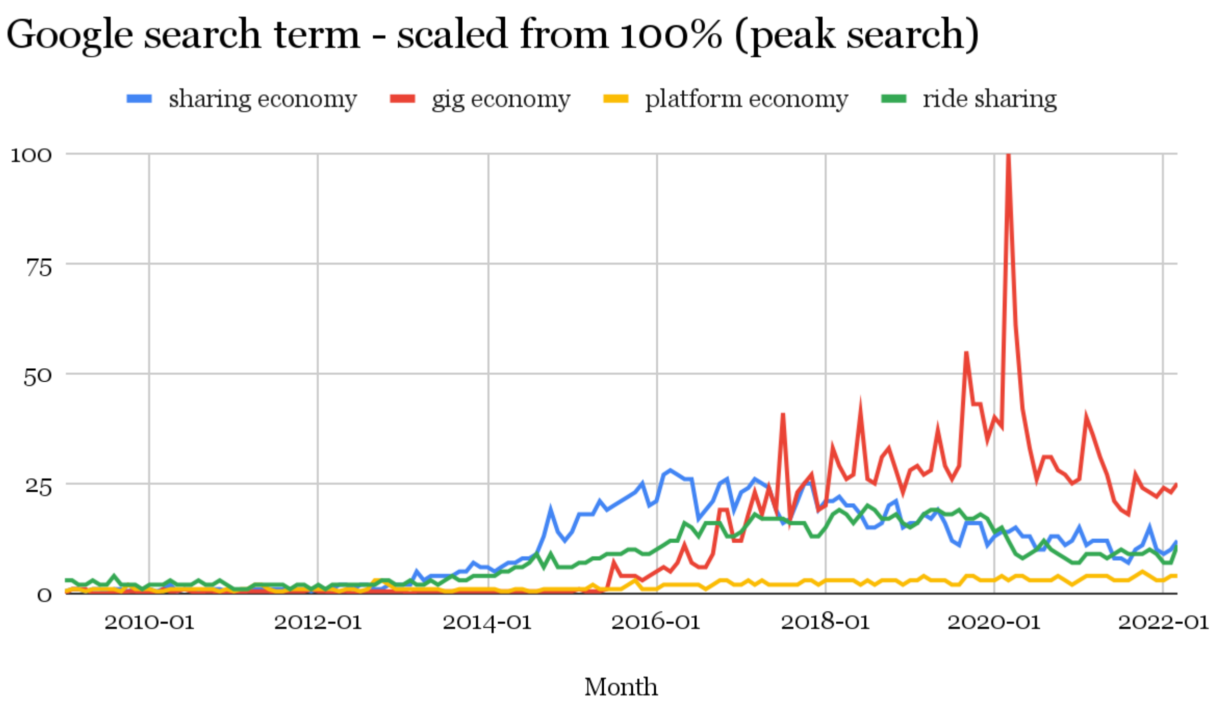
Over the last decade, platform work has generated a lot of interest (and frankly, concern) among policymakers and labor market researchers, sparking considerable efforts to measure and study its effects. Yet there is still much that is unknown about platform work. As an emerging field of study, much of the existing literature relies on qualitative methods such as interviews to understand the experiences and conditions of platform work (Altenried, 2021; Josserand & Kaine, 2019; Kaine & Josserand, 2019; Montgomery & Baglioni, 2020). Large N studies on platform work have either relied on direct, larger scale surveys of platform workers, usually by focusing on a few large platform companies to gain access to survey respondents (Berg & Furrer, 2018), or they have used wide-net, one-off surveys to capture the proportion of gig workers among a population (Lepanjuuri et al., 2018; Urzì Brancati et al., 2020). Studies such as these are extremely valuable for understanding the characteristics of platform workers and their working conditions, but they are less valuable in helping connect platform work and its possible effects beyond working conditions. Thus, quantitative research connecting platform work to other social science fields such as public health, politics, family, and gender are especially limited.

Given the state of the emerging research in this area, I will focus my review of the research on two main areas: first, summarizing the state of known participation rates of platform work and characteristics of platform workers derived from the current research, and then second, reviewing relevant theories that tie work conditions and life stages to political interest and participation. This section will end with a short evaluation on how platform work and political participation dynamics has played out in the UK context, before turning to my main research questions and hypotheses.

2.1 What is platform work, and why should we be worried about it?

As a newcomer to the labor market, platform work can go by many different names: "crowdwork," "sharing economy," and probably most popular "gig economy."[1] A quick consultation of Google search trends (Figure 1) indicates very little discussion of platform work prior to 2010, then in the early 2010s, "sharing economy" starts to pick up, tracking closely with "ride sharing," which makes sense: Uber, one of the breakout platform economy players, started operating in 2010 and Lyft shortly after in 2012. In recent years, the term most widely adopted among the public seems to be "gig economy," which peaked dramatically in Google searches in March 2020, aligning with the declaration of COVID-19 as a global pandemic and the beginning of extensive lockdowns.

Figure 1. Google search trends for popular platform economy terms



Data source: Google Trends (https://www.google.com/trends), my own illustration.

While the COVID-19 pandemic appears to have been instrumental in raising public awareness of the challenges, opportunities, and possible dangers of platform work and other "essential work," interest among social science researchers pre-dates the pandemic. It's easy to see why: as Urzì Brancati and colleagues (2020) wrote in their report on the COLLEEM II survey results for the European Commission Joint Research Centre, digital platforms often lack clear legal status. This ambiguity has implications for consumer protection, employment protection, and taxation policy, made all the more complex in the case of international

[1] Note that I use platform work and gig work interchangeably throughout.

platform companies operating across differing regulatory contexts (Urzì Brancati et al., 2020).

Not only is the legal status of digital platform companies unclear; the scope of what counts as platform work seems difficult to pin down, which creates significant challenges for research and policy development. Many definitions agree that a platform service connects multiple parties through a digital platform (Riso, 2019), which both algorithmically matches freelance service providers with clients and facilitates transactions between them (Riso, 2019; Urzì Brancati et al., 2020). This definition fits well in the context of services like Uber, which match riders with drivers, or TaskRabbit, which matches manual workers with household or business clients, or digital workers using Amazon Mechanical Turk to find short-term, online paid work. Other definitions emphasize the "network effects" of platforms, which describes the process of a platform becoming more useful as it becomes widely adopted (Riso, 2019), which raises the potential for digital platforms to crowd out more traditional services (Flakin, 2021) and erect higher barriers to market entry for additional platform companies**.** Finally, most definitions of platform work describe the status of the platform worker as a freelancer or independent contractor. This conception of gig work implying greater individual autonomy is often highly contested, however; given the power differential between the worker and the platform company, some describe gig work as a "hybrid employment relationship," wherein the platform still exerts considerable power over the worker's time and work (Montgomery & Baglioni, 2020), yet at the same time does not in turn offer the types of social protections typically associated with regular employment, such as a legal contract, health insurance, pension, etc (Howson et al., 2021).

Given definitional disputes and the diversity of work that can be classified as "platform work," measuring rates of participation among the working population is fraught with challenges. O'Farrell & Montagnier (2020) identify three main difficulties inherent in surveying the public on platform work involvement. First, the concept of "platform work" has proven difficult to explain to survey respondents, and there is some evidence that platform workers themselves do not identify with the term (Montgomery & Baglioni, 2020). Second, there are differing definitions of platform work across surveys and country contexts (e.g. different relevance periods for engaging in platform work, ranging from past two weeks to past year). Finally third, platform workers are still a relatively small group, requiring a very large sample size to capture. Panel studies like the German Socioeconomic Panel (SOEP) or the UK Longitudinal Study (UKLS) can be well-suited to capturing platform work participation rates, since they work with very large sample sizes, but adding these types of questions takes time: time for testing question validity with a smaller sample, time for validating and compiling the results, etc. This thesis uses data from the UKLS, which added gig economy questions for the first time in 2020; the SOEP also added questions to their v37

2020 survey, but as of writing this in spring 2022, have only just now released the results, which speaks to the time it takes to get these types of insights.

Outside of panel data studies, there have also been large, one-off online surveys to capture platform work, such as the COLLEEM survey mentioned above, but online surveys are subject to a degree of selection bias, which in this case could possibly overestimate the prevalence of platform work, given that platform work can only reasonably be undertaken if one has regular internet access (O'Farrell & Montagnier, 2020; Urzì Brancati et al., 2020).

Given the challenges of measurement, reported rates of participation in platform work in Europe vary: the COLLEEM II 2018 survey estimated that only 1.4% of those surveyed did platform work as their main occupation, with an additional 7% doing platform work for supplementary income, across 16 EU Member States (Urzì Brancati et al., 2020). In the UK, the NatCen Panel 2017 found that 4.4 percent of the population had worked in the gig economy in the previous 12 months (Lepanjuuri et al., 2018). Another online survey completed by the National Social Security Institute (INPS) in Italy found that only about 0.5% of the Italian working population uses platform work for their primary source of income, with an additional 1.5% for supplementary income (Cirillo et al., 2021). However, while the rates of participation seem to be low, and past data sparse, most sources seem to agree that the number of platform workers is growing (Cirillo et al., 2021; Urzì Brancati et al., 2020).

2.1.1 The conditions of platform work

At least two major surveys have been conducted to understand the experience of platform work. First, there is the International Labour Organization's INWORK survey on crowdwork, which was one of the earliest efforts to capture the conditions of platform work. It surveyed 3,500 workers in 75 countries working in one or more of the five major, globally operating microtask platforms: Amazon Mechanical Turk, Clickworker, Prolific, Microworkers, and CrowdFlower. The second major survey is the already-mentioned COLLEEM II online survey, which gathered 38,022 responses across 16 EU Member States. The ILO survey is particularly detailed on conditions of crowdwork while also sidestepping some measurement issues (since the sample consists of known crowdworkers), whereas the COLLEEM survey benefits from a much larger sample and encompasses the wider category of platform work.

ILO conducted two surveys, in 2015 and 2017, and among many findings, reported the following working conditions trends: low wages, low social protection, insufficient availability of work, and long and/or atypical working hours (Berg & Furrer, 2018). The COLLEEM II survey, conducted in 2018, similarly reported a high prevalence of long hours and atypical working hours, as well as a high prevalence of pay-per-task income (rather than regular income) (Urzì Brancati et al., 2020).

Across all regions surveyed by the ILO, the majority of crowdworkers earned significantly less than their country's minimum wage, especially when "unpaid work" (defined in the report as time spent searching for jobs, earning credentials, completing reviews, etc) is taken into account. Yet despite the low pay, a substantial number of those surveyed reported that their crowdwork wages were an essential source of income, with up to two-thirds reporting that it was necessary for meeting their basic needs (Berg & Furrer, 2018). Urzì Brancati and colleagues (2020) similarly found high rates of unpaid work due to the nature of most platform work being pay-per-task or per-task-time (e.g. driving around in an Uber, waiting for fares).

On average, only 60% of crowdworkers surveyed by ILO had access to health insurance, and in most of those cases, that coverage was provided through family members. Further, Berg & Furrer (2018) observed that high dependence on crowdwork wages had an inverse relationship likelihood to have access to social protection coverage, with unprotected workers more likely to report high dependence on crowdwork wages.

Finally, platform workers tend to work long and/or atypical working hours. The ILO survey had 52% crowdworkers reporting working 6 or more days a week, 43% working during the night, and 68% in the evenings (Berg & Furrer, 2018). Urzì Brancati and colleagues found that around two-thirds of platform workers provide services on weekends and nights. Often platform workers also have day jobs, which in part explains the late hours, but often the hours were dictated by some of the idiosyncrasies of the work itself, including managing different time zones when searching for online tasks, or providing service, deliveries and transportation (e.g. evening food delivery). Thus, long hours and unusual schedules are yet another possible driver of disadvantage that proceeds from platform work (Cirillo et al., 2021).

The low wages, long hours, and unpredictability of platform work can very negatively affect workers' overall sense of wellbeing. In their review of gig economy work experience research, Kaine and Josserand (2019) point out high reported rates of anxiety among platform workers, along with an "emotional oscillation" associated with highly volatile income flows. They also discuss the many types of risk associated with platform work: there is the lack of safety net already discussed, but then there is also the risk associated with providing one's own capital to participate in platform work (for instance, Uber drivers providing and risking their own vehicles) (Kaine & Josserand, 2019). Furthermore, there is a health and safety risk associated with some types of platform work, made all the more risky by the limited liability that platform companies have in ensuring safe working conditions.

2.1.2 Who chooses to enter into platform work, and why?

Given the tough working conditions and relatively low payoff, who then elects to enter into platform work? The stereotypical platform worker is usually described as younger, male, and more likely to have a migrant background. The UK's Department for Business, Energy & Industrial Strategy's report on gig economy workers backs up these impressions on age and gender, reporting that among gig workers they surveyed, 56% were ages 18-34 and 54% were male (Lepanjuuri et al., 2018). The ILO reported that the average age of crowdworkers surveyed in 2017 to be 33.2 years old, and two-thirds of them male, with a stronger male skew in developing countries (Berg & Furrer, 2018).

Further, platform workers have been found to be more likely living in urban centers and they tend to have similar levels of education compared with the general public, per the NatCen Panel (Lepanjuuri et al., 2018). The ILO similarly reported that crowdworkers are well-educated, with fewer than 18% having a high school diploma or lower and 57% reporting a bachelor's degree or higher (Berg & Furrer, 2018).

Finally, platform workers are more likely to have a migrant background than in the general working population. The COLLEEM II survey found that the proportion of foreign-born respondents is twice as high among platform workers compared with the total sample (around 15%, vs 7.7% of the total sample) (Urzì Brancati et al., 2020). They are also more likely to live in larger households and have dependent children (Urzì Brancati et al., 2020).

So what are the drivers for entering into platform work? Unsurprisingly, the most highly cited reason is a desire to earn additional income (Berg & Furrer, 2018; Lepanjuuri et al., 2018; Urzì Brancati et al., 2020). Schedule and location flexibility is another often-cited reason, particularly for digital crowdworkers (Berg & Furrer, 2018). Taken together with the data showing strong prevalence of foreign-born workers and workers with dependent children among platform workers, financial need appears to be a very strong driver, in particular for those who require flexible schedules (e.g. parents) and those who are otherwise limited in their earning potential (e.g. immigrants whose credentials might not be recognized in their residing country).[2]

2.1.3 Acknowledging heterogeneity among platform workers

Having established some of the similarities found among gig workers, it is essential also to understand major points of difference. In their qualitative study involving 112 interviews with workers across seven different platforms in the US, Schor and colleagues

[2] Indeed, there are growing concerns that the increase of foreign-born platform workers in Europe could be a sign of increasing labor market segmentation, with foreign-born workers overrepresented in secondary labor markets characterized by low skill work, high job instability, involuntary underemployment, and low satisfaction with work (Grubanov-Boskovic et al., 2017).

(2020) observe two main axes of variation among platform workers: first, economic dependence on gig income, and second, the degree of skills required for certain types of work. To the first, they distinguish between those who depend on gig income, vs those for whom it is more supplemental. The former group describes a more precarious existence: lower work satisfaction, less freedom to turn down work requests, and higher rates of anxiety over erratic earnings, while the latter report higher rates of satisfaction with platform work, citing the appeal of flexible work (Schor et al., 2020). To the second differentiation, Schor and colleagues (2020) find that skill requirements create a kind of hierarchy across both platforms and types of work, with some higher-skilled gig jobs like design work, life coaching, and software programming earning sizable compensation at the top, but with the majority of gig jobs ranging from middling to very low pay for lower-skilled work. I will return to these distinctions—skilled work vs less skilled, and dependence on gig work—in my analysis, to distinguish different ways gig work might relate to political participation.

2.2 Theories of Political Engagement

There is extensive research that explicitly ties work conditions to political interest and voter turnout. I will first examine the influential Resource Model Theory, proposed by Brady, Verba, and Schlozman (1995). The Resource Model Theory lays out key variables that enable different types of political participation: money, time, and civic skills. I will then extend the Resource Model Theory to discuss the importance of political socialization, as discussed by Emmenegger and colleagues (2017), Armingeon and Schädel (2015), and Schäfer and colleagues (2020). The socialization account emphasizes the social determinants of political interest, in particular the importance of work-related experiences in young adulthood. Finally, I will briefly discuss the concept of "precariousness," articulated by Standing (2011) and Kalleberg (2018), who observe that growing "casual work" trends are driving the creation of a new, underserved social class, with implications for the current political landscape in wealthy democracies.

2.2.1 Resource Model Theory and Voting: The importance of time, money, civic skills

Brady, Verba, and Schlozman's Resource Model Theory proposes three resources that, taken together, can impact both the level and type of an individual's political participation: money, time, and civic skills (Brady et al., 1995). Money directly enables donations to campaigns, whereas time enables volunteering for political campaigns and becoming informed on political issues. Civic skills are developed in spaces where the individual has the opportunity to demonstrate leadership or organizational skills, for example as a member of church, or within the workplace. The key determinant seems to be whether the individual takes part in work where they must exercise higher-order thinking and leadership skills. All three resources therefore strongly relate to one's occupation: does one's work allow enough financial stability, free time and flexibility in schedules, and opportunities to practice civic skills to participate politically?

2.2.2 Socialization, Voting, and Political Interest: The importance of work and age

The socialization account of political participation centers the development of political interest as key to acts of participation. While Brady and colleagues also discuss political interest as a determinant of political participation, they do not connect work-related experiences with political interest; rather, they see political interest as a mediator between education and voting (Brady et al., 1995). Emmenegger and colleagues (2017) explicitly connect work and political interest by way of socialization, which suggests that age is an important factor in the degree to which experiences shape political interest. Specifically, individuals tend to be much more malleable during their adolescent years, and thus any experiences, good or bad, during these years tend to have an outsize and lasting impact on that individual's political interest. Emmenegger et al. (2017) build off this understanding to suggest that unemployment, shown to depress political engagement in general, is most detrimental when experienced at a young age. In contrast, while older workers who experience unemployment might see an immediate drop-off in their levels of political interest, they soon "rebound" to their previously-held interest, suggesting that political interest becomes more resilient with age (Emmenegger et al., 2017).

In another examination of the importance of socialization for political participation, Armingeon and Schädel (2015) consider how the rise of "individualization trends" and the decline of social cohesion in the workplace (e.g. the decline of unions) has possibly contributed to decreasing voter turnout and increasing political inequalities in Europe, particularly among lower classes. Schäfer and colleagues (2020) connect the individualization trends explored by Armingeon and Schädel to their outsize impact on young people, who are experiencing a rising "start-up" cost to first-time voting compared with earlier generations who benefitted from the resources provided by stronger social organizations. Similar to Emmenegger and colleagues' findings on political interest, they find that abstaining from voting in one's first election has an outsize impact on the individual's likelihood to vote in future elections, suggesting that voting is a habit formed at a young age (Schäfer et al., 2020).

From the platform work perspective, one can see how low wages, long hours, and limited professional growth opportunities could plausibly have an adverse effect on political engagement, vis-à-vis the Resource Model Theory and the socialization perspective.

2.2.3 Efficacy, Insider-Outsider Dualism, and Precariousness

A significant part of the political participation literature focuses on two types of efficacy with respect to voting: internal and external. Internal efficacy refers to one's own feelings about their political competency (i.e. their self-esteem, politically), and external refers to whether one feels their interests are actually represented by their voting options. Emmenegger and colleagues (2015) connect the idea of internal efficacy to the workplace through this notion of a "spillover model," wherein if an individual's job experiences lower his self-esteem and sense of control over his life, this can "spillover" into his assessment of his own political competences. This low political self-esteem can then lower motivation to vote. Further, adverse workplace experiences can also lower one's sense of external efficacy by making one feel like an outsider, not represented by political elites (Emmenegger et al., 2015). This connects to the "insider-outsider dualism" theory investigated by Rovny and Rovny (2017), who found that labor market outsiders (and it follows, those who feel they have low internal and external efficacy) are more likely to abstain from voting.

This concept of internal/external efficacy connects strongly to the "precarious work" dialogue in labor market research. Briefly, precarious work is understood to be characterized primarily by long term financial and social instability, usually proceeding from underemployment with diminished social protections (Kalleberg, 2018; Standing, 2011). According to those who investigate precarious work, it goes beyond simply anxiety about financial insecurity: it is a deeper experience that influences one's identity, feelings of self-worth, and sense of future (Standing, 2011). Politically speaking, precarious work can lead to extreme alienation from and distrust of existing power hierarchies, and a stronger likelihood either of abstaining, or of voting for populist and/or neo-fascist candidates who promise the kinds of protections that the free market has failed to provide (Standing, 2011). Kalleberg (2018) describes the "precariat" options for social and/or political self-expression as either exit, loyalty, or voice. Exit is resigning oneself to a marginalized economic position, and disengaging from public and political life. Loyalty is the flipside of exit: taking on a kind of rugged individualism and looking out for oneself. Finally, voice is the solidaristic option: taking part in group protest against perceived sources of inequality (and here, this can go in multiple ways, from leftist class-consciousness all the way to far right ethno-nationalism). For many who write about precarious work, gig work is an indistinguishable part of this larger labor market creep towards temporary and unprotected work (Montgomery & Baglioni, 2020), and thus we could expect that those who undertake gig work might exhibit these same types of political behavior and expression.

2.3 UK Platform Work and Political Participation

The UK is an interesting context for studying gig work for at least two reasons. First, the gig economy is relatively well developed in the UK. As a rich, liberal market economy, the UK offers a promising market for platform companies to enter, with its business-friendly regulatory environment and a large, highly urbanized population fueling both the demand for and supply of on-demand service provision. Growing insecurity in the UK labor market, due in large part to the UK's commitments to neoliberal deregulation of the labor market since Thatcher, has pushed workers to take on casual work with no guaranteed hours or seek self-employment (Taylor, 2021). Further, policy experiments in the UK tying welfare benefits to work (so-called "workfare") have also pushed individuals to seek employment at all costs (Kalleberg, 2018). As a result of these regulatory and labor market factors, as well as a swell of venture capital funding the expansion of platform-style employers, participation in platform work has grown rapidly in the UK. The Oxford Internet Institute's Fairwork Project estimates that the percentage of the population taking part in platform work has more than doubled in the last five years: 4.4 million workers or 16% of the adult population of the UK (Howson et al., 2021). In contrast Germany, a close neighbor with a comparably-sized economy, has an estimated 12% of employable people (note: only a subgroup of all adults) having done gig work at least once (Oğuz Alyanak et al., 2021).[3]

Second, it is impossible today to discuss the future of the UK without considering how Brexit might have an impact, and indeed, regulation of the platform economy is yet another area where we can expect policy divergence from the EU. Regulating the platform economy has gained significant traction in the EU,[4] whereas in the UK, political leadership continues to voice support for labor market deregulation (Taylor, 2021). Thus, it looks likely that platform economy developments in the UK will gain particular policy relevance, providing a contrasting example to the EU's regulatory approach (Florisson, 2021).

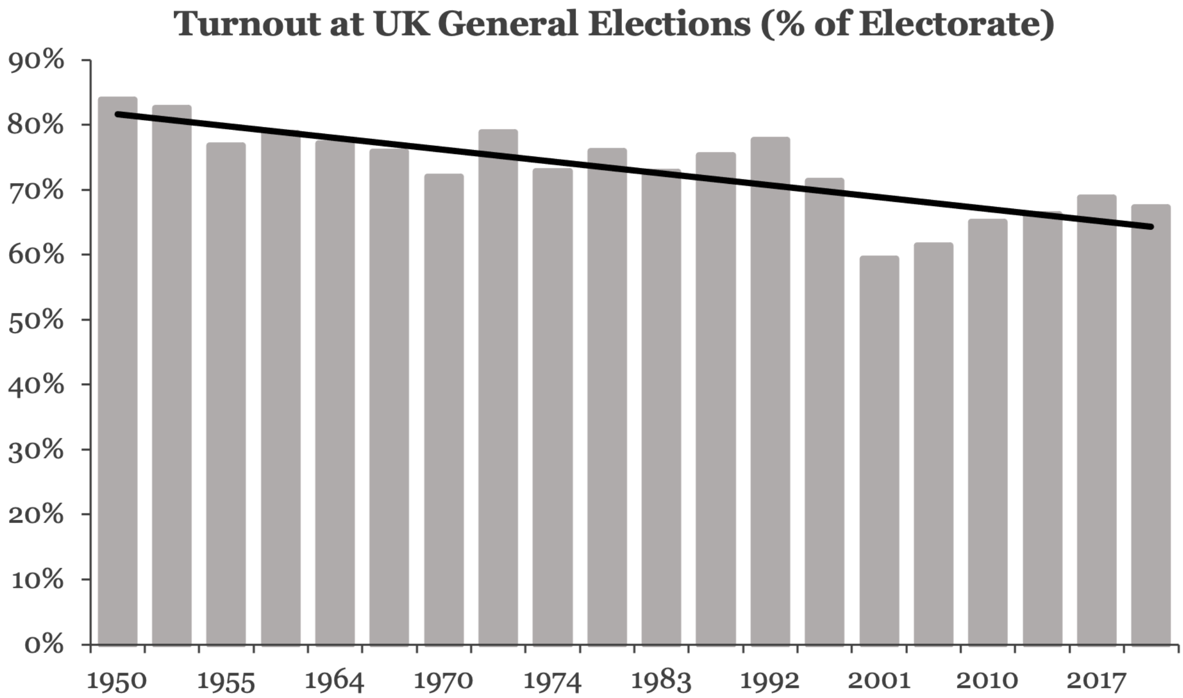
Turning now to political participation, like many wealthy western democracies, the UK has seen a distinct decline in overall voter turnout in general elections over the last 70 years (Fig. 2), as well as growing political inequality. Young people, ethnic minorities and migrants are less likely to be registered to vote compared with older, ethnically white, British-born residents, while unskilled workers and long-term unemployed people are more likely to report feeling politically disengaged (Uberoi & Johnston, 2021). MPs are also starting to look more different from their constituents, becoming overall older, more educated, and less likely to come from lower occupational classes (Uberoi & Johnston, 2021).

[3] Note again here the differing definitions of platform work participation. Here, the question is "ever participated," compared with earlier discussed rates of participation that attempt to capture platform work as a main source of income, completed platform work in a given period of time, etc.

[4] As of writing this in April 2022, the European Commission recently closed public comment on Draft Guidelines which will extend EU competition law to enhance the bargaining rights and working conditions of "solo self-employed persons" (European Commission, 2021).

Platform work could act as a possible accelerator of these trends, since platform workers tend to be younger, of migrant background, and since "outsider" work status is thought to connect to one's sense of political agency (Rovny & Rovny, 2017).

Figure 2. Bar chart showing declining voter turnout in the last 70 years in the UK



Data source: House of Commons Library (2021), my own illustration

2.4 Research Questions and Hypotheses

My first research question (RQ1) focuses on the same topic that previous studies have sought to address: what are the socio-demographic characteristics and working conditions of platform workers in the UK? This question is important to answer first before looking at political outcomes, as it is clear from previous studies that platform workers often look quite different from the general population in terms of their socio-demographic identities and work experiences.

Relatedly, I also pose RQ2: how are gig workers different from each other, and can they be sorted into a clear typology? This question is informed by the qualitative study by Schor and colleagues (2020), who delineated between those who are dependent on platform work or not, and distinguishing high-skill from low-skill work.

Given the differences outlined in RQ1 and RQ2, and taking into account known predictors of political outcomes from the literature, I then ask RQ3: how does platform work itself impact an individual's likelihood to be politically interested and turn out to vote?

Thus, I will test the following hypotheses:
Confirmatory
- (H1) Participating in platform work reduces an individual's overall political interest.
- (H2) Participating in platform work reduces an individual's likelihood of voting.

Exploratory
- (H3) The impacts of platform work on political interest and voting are heterogeneous based on the type of work performed and the extent to which the individual relies on gig work income:
  - (H3.1) Completing manual vs non manual gig work: I hypothesize that manual gig work will have a greater negative impact on political interest and voting than non manual gig work.
  - (H3.2) Relying on gig work vs casual gig work: I hypothesize that relying on gig work will have a greater negative impact on political interest and turnout than casual gig work.

The Resource Model Theory, socialization, and the concept of precariousness inform H1 and H2:
- If platform work tends to be low wage, shortens workers' free time, and reduces opportunities to practice civic skills in the workplace, platform work should depress likelihood of voting.
- If gig workers tend to be younger, gig work could have an outsize impact on their political interest.
- If platform work generates feelings of being an outsider in workers, then this could also depress voting.

Finally, H3 borrows from the findings of Schor and colleagues (2020), who observed differences in outcomes among different categories of gig work. In particular, I am interested in the degree to which precarious work and low-skill work expresses itself in political participation outcomes.

3. Data and Methods

3.1 Data Source

This study uses Wave 11 of Understanding Society: the UK Longitudinal Study Main Survey, which consists of 32,006 UK adult residents surveyed in 2020 and is the most recent available wave as of writing (UK Data Service, 2022). Wave 11 is the first year that the UKLS collected data on participation in gig economy work, including type of gig work completed, number of hours worked, and income earned. The UKLS also includes important political outcome variables such as voting in the previous election and political interest, as well as socioeconomic and working conditions variables that will serve as controls.

3.2 Methods

My empirical analysis is divided into three main sections: first, I will estimate the likelihood of selecting into platform work across likely covariates. For this, I will use Probit regression modeling to estimate probabilities of taking part in gig work (RQ1). In order to shed additional light on the heterogeneity of characteristics amongst gig workers themselves (anticipating H3), I will also estimate and compare probabilities between casual gig workers and those who rely more heavily on gig work income, as well as compare manual and non manual gig workers.

Second, I will turn to my relevant outcome variables: political interest and voter turnout. Political interest is coded as a simple binary, and as voter turnout is binary as well, both outcomes are estimated with Probit regression models, with gig work as the treatment. I first estimate the naive differences between gig workers and non gig workers, then add covariates in a nested model approach, including/excluding covariates grouped into socioeconomic characteristics, precarious work, and for estimating political interest, migrant status and voting rights. I will also analyze the treatment effects of each category of gig work: non-manual, manual, casual, and reliance. I will use conventional measures to determine significance (p-values of < 0.1, 0.05, and 0.01).

Third, as a robustness check of my Probit model estimates, I will use Propensity Score Matching (PSM) to create a matched dataset to estimate the effects of gig work on political interest and voter turnout. Since selection into gig work is highly likely to confound the relationship between gig work and political engagement (e.g. financial insecurity impacting both likelihoods of being a gig worker and voting), PSM is a good option for explicitly matching comparable non gig workers with gig workers, while disregarding highly irrelevant control units. Since there is limited overlap between gig workers and non gig workers and gig workers are the extreme minority in the sample, the estimates will thus represent the Average Treatment Effect for the Treated (ATT).

All analyses are conducted in R using RStudio (R Core Team, 2020).

3.2.1 A note on interpreting Probit models

Much of what I will present are Probit coefficients, and as such they should be interpreted as changes in z-score in the probability distribution of the outcome (Moore, 2013). Unlike linear models, where the coefficients can be understood as a rate of change and calculating predicted outcomes is simply a matter of plugging in values, Probit coefficients take into account the variance of the underlying latent propensity of the outcome, which is unobserved and can change across model specifications (Karlson et al., 2012; Moore, 2013). What this means is that there are limits to interpreting nested Probit models, as it is difficult to ascertain whether changes in the treatment coefficient between models are due to the added covariates, or due to changes in the underlying propensity variable distribution between model specifications. To help clarify this and provide a more substantive interpretation, I will also provide predicted marginal probability changes of certain models. Furthermore, I will aim to restrict my coefficient interpretations to direction of effect (positive or negative, i.e. increasing or decreasing probability), and relative size comparisons of estimates within models and across models with the same covariate specifications, but different treatment (i.e. across the categorizations of gig work).

Finally, this paper does not discuss Log Likelihood or Akaike's Information Criterion (AIC). I do report these values for transparency and for the interested reader to observe changes in model fit, however.

3.3 Variables, Definitions, and Missing Observations

3.3.1 The treatment variables

The main treatment variable is binary, taking the value of 1 if the respondent completed any kind of platform work in the month prior to the date of interview (N = 397). Respondents then select from the following types of work: carried passengers in a vehicle (N = 90), delivered food or beverages (N = 50), provided courier services (N = 32), performed general manual tasks such as cleaning (N = 158), and finally performed non-manual tasks, such as writing software or editing (N = 174) (UK Data Service, 2022). Respondents are also asked for the number of hours they typically work in a month (mean = 17.9). With these two additional layers of information, I coded four secondary treatment variables: relying on gig work (anything above 20 hours/month, N = 190) vs. casual gig work (N = 207), and non-manual vs. manual gig work (N = 243 and N = 174). Here I am assuming that more hours implies a higher reliance on gig income, and that there are sizable average differences in education, resources, background, and work experiences between those who do, say, copyediting, vs those who take delivery jobs. These categorizations are an adaptation of the typology proposed by Schor and colleagues (2020), though it must be said that the design of these categorizations (particularly relying on gig work) is somewhat arbitrary, based on my intuition and what would show meaningful difference given the data distribution.

My control group is all Wave 11 survey participants who reported not completing gig work in the prior month (N = 31,662). This group includes those who said they were in paid employment (N = 17,653) and those who said they were not (N = 13,844). Interestingly, 135 gig workers (34%) reported not being in paid employment, despite reporting that they had earned gig income in the last month (mean = 15.4 hours). Given this high rate of claiming no paid employment among gig workers, I decided to use the entire sample of non gig individuals as my control group,[5] rather than limiting my controls to those who reported being in paid employment. As a robustness check for my results, I also estimate effects on a dataset where the control units were filtered to paid employment (see Appendix: Tables S9-S11).

3.3.2 Outcomes and potential issues

The coding of the two main outcomes—political interest and voting as binary variables—has already been discussed, though it should be noted that both have significant missingness in the dataset, particularly voting. This appears to be due largely to political questions being added midway through survey collection for 2020, in order to measure participation rates in the 2019 European Elections and the 2019 UK General Election (UK Data Service, 2022). Relatedly, as the survey collection was taking place during the early months of the pandemic, this required a shift in strategy in survey collection, with most respondents moving from in-person interviews to phone or online surveys; this disruption led to marked differences in participation rates from previous years and undoubtedly had an impact on response rates for voting, which is captured in a voluntary self-completion module. Table 1 contains the study variables with highest rates of missingness. To partially overcome the especially high rates of missingness for voting, I rely on a single imputation strategy using deterministic Probit regression-based imputation, incorporating UKLS data from the 2017 voter turnout rates (Waves 9, 10), as well as known covariates that impact voting, to predict an individual's likelihood of voting (Kalton & Kasprzak, 1986).

Table 1. Study variables with high rates of missingness among non gig workers and gig workers, along with p-value significance of difference.

Missing Variable	**Gig Work = 0** (% Missing)	**Gig Work = 1** (% Missing)	**P value**
Voted 2019 Election	55.07	56.68	0.52
Political Interest	28.88	28.21	0.77
Migrant Status	18.23	14.61	0.04
Can't Vote	9.52	12.34	0.09
Second Job	1.94	0.25	0.00
Self-employed	0.21	0.50	0.41

It should be noted that estimates of voter turnout should be taken with a sizable grain of salt. The uncertainty of imputation aside, self-reporting on participation in elections is

[5] Note that I use "non gig worker" throughout to describe this control group. This is not to imply that they are "workers," but refers to their state of selecting "No" to the gig work survey question.

subject to at least two sources of bias: that voters are more likely to be captured in survey samples, and survey participants are more likely to misreport voting when they did not (Selb & Munzert, 2013). Therefore, we should assume that across our sample, voter turnout has an upward bias, though my hope is that observed differences in voting likelihood between treatment and control still represent real differences in the population.

3.3.3 Control Variables

Table 2 gives an overview of the control variables relevant for this study. The first group of variables comprise known covariates that influence political interest and voting through the Resource Model and Socialization theories, particularly age, education, and income (Brady et al., 1995; Emmenegger et al., 2015, 2017). Note that age is treated as a binary variable of being under or over age 26, which helps facilitate age proportion comparisons between different types of gig workers in part 1 of the analysis. This age cutoff reflects the findings of Neundorf and colleagues (2013), who used the German SOEP study to show that political interest appears to grow in a linear fashion through young adulthood, but then stabilizes after age 25.

The second group of controls speaks to precariousness: being self-employed, self-reported feelings of financial difficulty, and having a second job (Kalleberg, 2018; Schor et al., 2020; Standing, 2011). In contrast to the first group of controls, these variables could be seen as effects of gig work themselves, and thus controlling them can produce post-treatment bias. However, controlling them can also help in exploring these variables as mechanisms, connecting gig work with political outcomes. To overcome this either/or problem, I will use nested model approaches that include and exclude variables in turn, to observe the relative changes in the treatment estimate.

The third group captures two elements of what I am calling “national/electoral inclusion”: having a migrant background (born outside of the UK) and not having the right to vote. These two variables do correlate (Pearson’s r of 0.12), but the UK also denies enfranchisement to individuals convicted of certain crimes, so the right to vote is not only a question of citizenship. Given that both of these variables have high rates of missing observations (see Table 1), these variables are not included in every model, to ensure that the effect sizes are not sensitive to missing observations, and note that those who cannot vote are filtered out for Part 3 of the analysis on voter turnout.

Table 2. Relevant control variables, their coding, and definitions

Control Grouping	Variables and Definitions
Socioeconomic/ Demographic	● Under age 26 - binary yes/no ● Gender - 1 Male/0 Female ● Monthly household income in £ (standardized in modeling) ● Has dependent children at home - binary yes/no ● Education ○ Higher education - any completion of university ○ High school - completed compulsory education ○ No qualifications (baseline)
Precariousness	● Self-employed - binary yes/no ● Financial difficulty - binary yes/no, self-reported feelings ● Second job - binary yes/no
National/Electoral Inclusion	● Migrant status - binary yes/no. Defined as having been born outside of the UK ● Cannot vote - binary yes/no.

Source: UK Longitudinal Study, Wave 11.

4. Findings

4.1 Summary Statistics

Summary statistics across all study variables, separated by gig worker status, are available in Table 3. A quick inspection already yields some interesting differences between gig workers and non gig workers in the sample: gig workers on average are 10 years younger, they heavily skew male, they seem comparably educated with respect to the control group, and they are more likely to have children, consider themselves self-employed, have a second job, and report financial difficulty. They are also more likely to have a migrant background and almost twice as likely not to have the right to vote.

Table 3. Main Study Variables by Treatment Status (Taking part in gig work)

		Gig worker (N=397)		Non gig worker (N=31662)			
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Diff. in Means**	**Std. Error**
Age (years)		40.5	16.5	50.4	18.8	9.9	0.8
Household Income/Month (£)		4596.8	2988.8	4315.3	2999.4	-281.5	153.7
		N	**Pct.**	**N**	**Pct.**		
Gender	Female	161	40.6	17598	55.6		
	Male	236	59.4	14064	44.4		
Under Age 26	26 or older	303	76.3	27579	87.1		
	Under 26	94	23.7	4079	12.9		
Education	High school	186	46.9	15364	48.5		
	Higher ed	181	45.6	13004	41.1		
	No qual	17	4.3	2816	8.9		
Children	Has child/ren	127	32.0	7261	22.9		
	No children	270	68.0	23933	75.6		
Self-employed	Yes	135	34.0	2300	7.3		
	No	260	65.5	29295	92.5		
Financial Difficulty	Yes	60	15.1	2225	7.0		
	No	336	84.6	28771	90.9		
Second Job	Yes	91	22.9	1411	4.5		
	No	305	76.8	29638	93.6		
Migrant Status	Yes	78	19.6	4109	13.0		
	No	261	65.7	21781	68.8		
	Missing	58	14.6	5772	18.2		
Has right to vote	Can vote	322	81.1	27580	87.1		
	Cannot vote	26	6.5	1069	3.4		
	Missing	49	12.3	3013	9.5		

Source: UK Longitudinal Study, Wave 11.

Table 4. Cross Tabulation of Gig Work Subgroups

	Manual	Non Manual	**Total**
Rely on Gig Work	132 (54.3%)	75 (48.3%)	207 (52.4%)
Casual Gig Work	111 (45.7%)	79 (51.3%)	190 (47.6%)
Total	243 (100%)	154 (100%)	397 (100%)

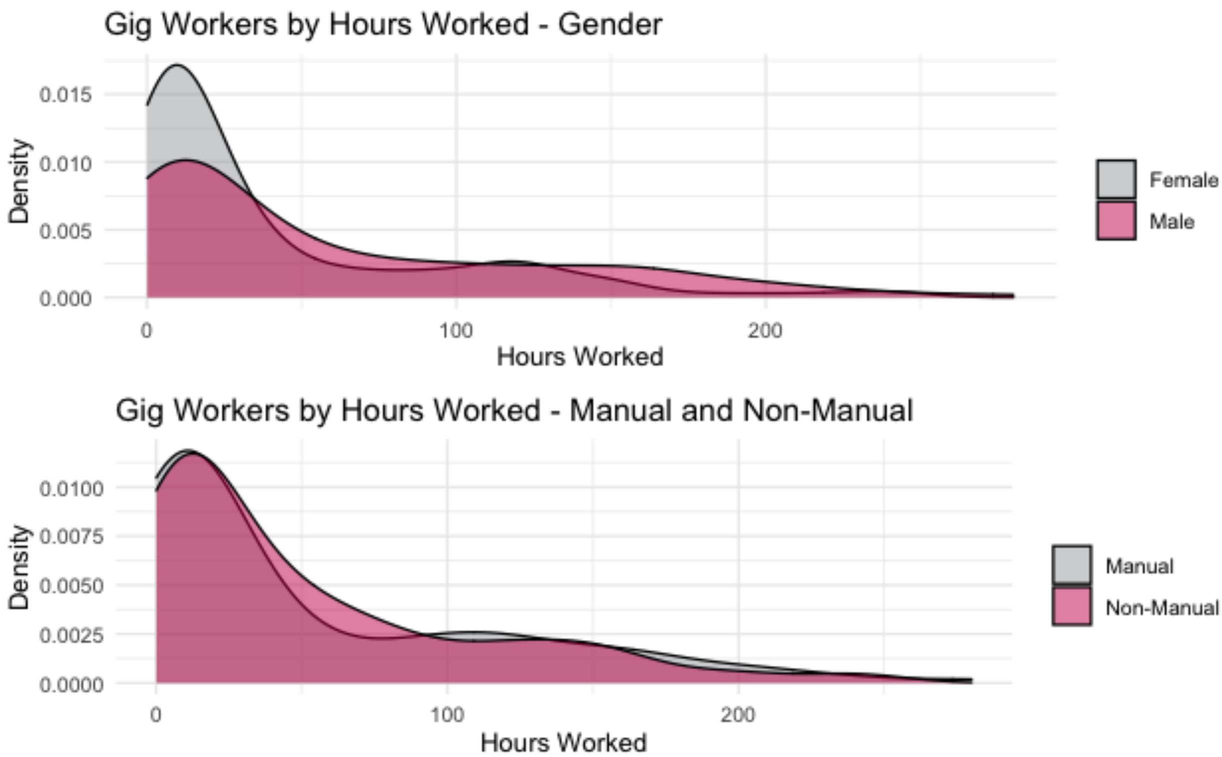
Table 4 is a simple cross tabulation of my two dimensions of gig work, to show overlap between the level of dependence on gig work and the manual/non manual division. There is fairly even distribution across the categories, with somewhat more manual workers being reliant on gig work than non manual workers.

Since age is an important element of political interest (and a potential confounder of its relationship with gig work), Figure 3 shows the distribution of age among gig workers and non gig workers, and then between our gig worker categories. As expected, gig workers skew younger than non gig workers, however the skew seems more due to casual gig workers than those relying on gig work.

Figure 3. Density plots by Age

Figure 4 considers the distribution of hours worked in a month, by gender and by manual/non manual workers. While gender's intersection with gig work is not explored in this paper, it is interesting to note that female gig workers seem to work fewer hours on average than male gig workers, suggesting that gig income is more supplementary for women than men.

Figure 4. Density plots of Hours Worked in a Month, by Gender and by Manual/Non Manual Work



4.2 Selection into Gig Work

Now let's turn to the first part of the analysis: what are the factors that predict entering into gig work? Table 5 shows the results of five Probit regressions: first, regressing gig work as a whole across likely predictor variables (model 1), and then predicting each category of gig work: casual (2), rely (3), non manual (4), and manual (5).[6] Comparing the Maximum Likelihood Estimates (MLE) of each variable in the model 1 is certainly interesting—here we can see that experiencing financial difficulty appears to be more strongly associated with gig work, when other covariates are accounted for—but what I find most interesting are the strong differences across gig work categories.

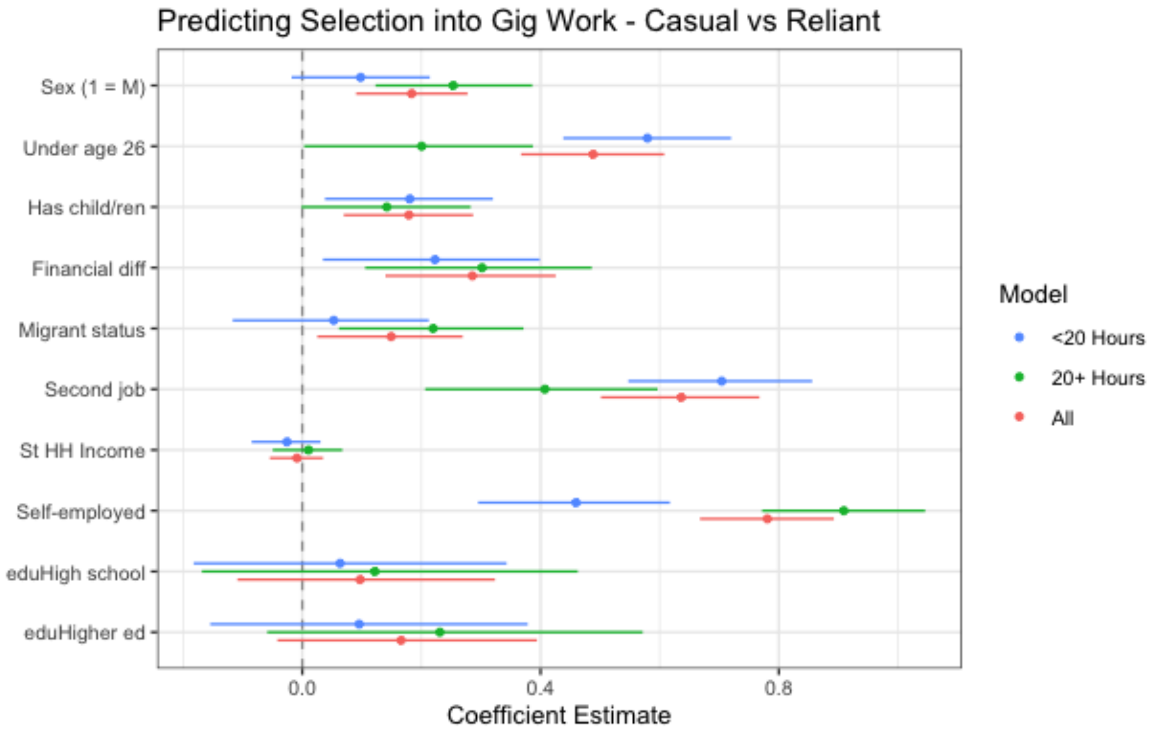
[6] Note that these models do include migrant status, despite the high levels of missingness. I include it here because I think it's important to capture the increased likelihood of gig workers coming from migrant backgrounds, an important vector of social inequality (Vandaele, 2020). As a robustness check, I ran models excluding migrant status to see whether the estimates change substantially, and the only sizable difference was a reduction in the estimated likelihood of expressing financial difficulty. See Table S2 in the Appendix for the full results.

Table 5. Maximum Likelihood Estimates for Selection into Gig Work

	Dependent variables:				
	All	Casual (<20hrs)	Rely (>=20hrs)	Non Manual	Manual
	(1)	(2)	(3)	(4)	(5)
Sex (1 = M)	0.184***	0.094	0.253***	0.111*	0.226***
	(0.048)	(0.059)	(0.067)	(0.066)	(0.058)
Under age 26	0.488***	0.576***	0.200**	0.375***	0.511***
	(0.061)	(0.071)	(0.098)	(0.087)	(0.072)
High school eqv	0.097	0.065	0.122	0.376	0.033
	(0.110)	(0.133)	(0.160)	(0.237)	(0.117)
Higher degree	0.166	0.096	0.231	0.633***	-0.081
	(0.111)	(0.135)	(0.159)	(0.235)	(0.121)
Has child/ren	0.179***	0.177**	0.142**	0.044	0.232***
	(0.055)	(0.072)	(0.072)	(0.077)	(0.067)
St. HH Income	-0.009	-0.025	0.010	-0.024	0.006
	(0.023)	(0.029)	(0.030)	(0.031)	(0.027)
Second Job	0.149**	0.047	0.220***	-0.028	0.269***
	(0.062)	(0.084)	(0.079)	(0.094)	(0.070)
Self-emp	0.636***	0.697***	0.407***	0.632***	0.511***
	(0.068)	(0.079)	(0.100)	(0.086)	(0.086)
Financial diff	0.781***	0.442***	0.909***	0.846***	0.623***
	(0.057)	(0.082)	(0.070)	(0.073)	(0.071)
Migrant status	0.286***	0.214**	0.302***	0.277***	0.240***
	(0.073)	(0.093)	(0.097)	(0.101)	(0.087)
Constant	-2.847***	-2.931***	-3.209***	-3.430***	-2.925***
	(0.111)	(0.134)	(0.163)	(0.237)	(0.120)
N	24,522	24,522	24,522	24,522	24,522
Log Likelihood	-1,484.815	-916.781	-756.828	-742.132	-989.120
Akaike Inf. Crit.	2,991.630	1,855.563	1,535.657	1,506.265	2,000.24

Note: ** p<0.1; **p<0.05; ***p<0.01*

Figure 5. Coefficient plots comparing maximum likelihood estimates across categories of gig work



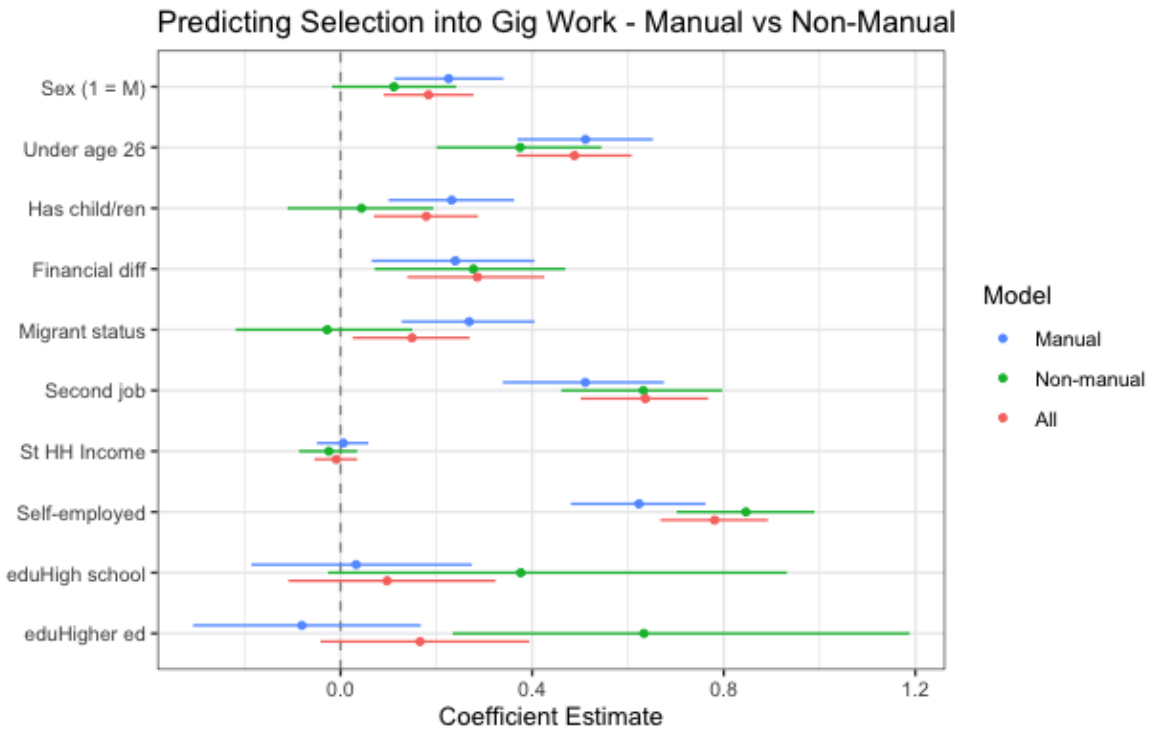


Figure 5 helps to visualize the differences across coefficients for each gig work category. Taking a look at the first plot, it is clear that while age is a strong predictor for gig work generally, it is much less predictive for those who rely on gig work (in green; the confidence interval almost intersects zero). Also those who rely on gig work are more likely to have migrant backgrounds; the same estimate for casual gig workers is small and insignificant. Moving to the second plot, it is clear that manual workers are more likely to have children than non manual workers, and that there is a wide educational divide between manual and non manual workers, with non manual workers far more likely to have completed some higher education. This calls into question the educational comparability between gig workers and non gig workers generally; it seems possible that this perceived comparability is more due to this subgroup of gig workers bringing up the average educational attainment.

These findings help validate the categorizations proposed by Schor and colleagues (2020), underscoring the importance of considering heterogeneity among gig workers when conducting analysis on gig work and its effects. Further, these findings provide some evidence to support Schor and colleagues' assertion that reliance on gig work means higher degrees of precarity; those who rely on gig work have somewhat higher rates of financial difficulty, are more likely to be self-employed, and are less likely to have a second job, implying more reliance on gig work, when other covariates are accounted for.

These findings help address RQ1 and RQ2. Socio-demographically speaking, gig workers in general tend to be male, younger, and have children, compared with the non gig workers in the sample. They are also more likely to fall into categories associated with precarity: reporting financial difficulty, being self-employed, and having two jobs. However, when gig workers are subdivided, notable differences surface, along lines of age, education, migrant status, and having dependent children.

4.3 Political Interest

Having validated the necessity of analyzing categorizations of gig work, let's turn to our first main outcome variable: political interest. Table 6 reports the naive MLEs on political interest across five predictor variables—all gig work, then the four gig work categories—using Probit bivariate regression. While these estimates are naive and thus should not be read as "true" estimates, it is still helpful to consider the initial differences between the groups. Interestingly, all gig work variables predict a positive impact on political interest, spelling danger for my H1, which predicted that gig work would have a depressing effect on political interest. That said, there are sizable differences among the estimates, particularly between non-manual and manual workers, with non-manual workers seeming to drive the overall positive effect on political interest and manual workers seeing no effect at all.

Table 6. Naive Maximum Likelihood Estimates of Political Interest on Gig Work

	Dependent variable:				
	Political Interest				
	(1)	(2)	(3)	(4)	(5)
Gig work - all	0.206***				
	(0.075)				
Casual		0.202*			
		(0.103)			
Rely on gig work			0.207*		
			(0.108)		
Non-manual				0.445***	
				(0.118)	
Manual gig work					0.037
					(0.094)
Constant	-0.060***	-0.059***	-0.059***	-0.060***	-0.058***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
N	22,802	22,802	22,802	22,802	22,802
Log Likelihood	-15,777.560	-15,779.410	-15,779.500	-15,774.030	-15,781.250
Akaike Inf. Crit.	31,559.110	31,562.810	31,562.990	31,552.060	31,566.500
Note:			*$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$*		

Next, I add covariates in a nested model format, with gig work (all) as the treatment variable. Table 7 reports the naive estimate first, then adds the socioeconomic controls (model 2), then switches to precarious controls (model 3), then to inclusion controls (model 4), then considering different group combinations before reporting the final model with all covariates (model 8). The MLE for gig work persists with socioeconomic controls, but reduces somewhat with the addition of the precarious controls, suggesting that precariousness might have a contributive effect on political interest. That said, the effect of gig work appears to remain positive, sizable, and significant as a predictor of political interest across all model specifications, providing strong evidence that H1 should be rejected. While gig work seems to have some kind of relationship with political interest, it was not in the direction that I expected (see Appendix: Table S3 for marginal probability changes for political interest across models).

Table 7. Maximum Likelihood Estimates of Political Interest on Gig Work

	Dependent variable:							
	Political Interest							
	Naive	Socioeconomic	Precarious	Inclusion	SE + Pr.	Pr. + Inc.	SE + Inc.	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gig work	0.206^{***}	0.236^{***}	0.158^{**}	0.240^{***}	0.203^{**}	0.188^{**}	0.277^{***}	0.249^{***}
	(0.075)	(0.081)	(0.078)	(0.084)	(0.082)	(0.087)	(0.090)	(0.091)
Under age 26		-0.352^{***}			-0.353^{***}		-0.331^{***}	-0.330^{***}
		(0.027)			(0.028)		(0.032)	(0.032)
Sex (1 = M)		0.378^{***}			0.380^{***}		0.372^{***}	0.374^{***}
		(0.018)			(0.018)		(0.019)	(0.020)
High school eqv		0.251^{***}			0.249^{***}		0.200^{***}	0.200^{***}
		(0.034)			(0.034)		(0.038)	(0.038)
Higher degree		0.728^{***}			0.720^{***}		0.684^{***}	0.677^{***}
		(0.035)			(0.035)		(0.039)	(0.039)
Has child/ren		-0.327^{***}			-0.321^{***}		-0.291^{***}	-0.287^{***}
		(0.021)			(0.021)		(0.023)	(0.024)
Second job			0.204^{***}		0.190^{***}	0.190^{***}		0.162^{***}
			(0.041)		(0.042)	(0.045)		(0.046)
Self-emp			0.177^{***}		0.073^{**}	0.177^{***}		0.077^{**}
			(0.032)		(0.033)	(0.035)		(0.037)
Financial Diff			-0.226^{***}		-0.165^{***}	-0.212^{***}		-0.155^{***}
			(0.034)		(0.035)	(0.037)		(0.039)
St HH Income		0.063^{***}	0.096^{***}		0.055^{***}	0.099^{***}	0.060^{***}	0.054^{***}
		(0.009)	(0.009)		(0.009)	(0.009)	(0.010)	(0.010)
Can't vote				-0.244^{***}		-0.276^{***}	-0.010	-0.014
				(0.045)		(0.047)	(0.052)	(0.053)
Migrant status				-0.137^{***}		-0.118^{***}	-0.131^{***}	-0.117^{***}
				(0.025)		(0.026)	(0.028)	(0.028)
Constant	-0.060^{***}	-0.533^{***}	-0.061^{***}	-0.014	-0.532^{***}	-0.018^{*}	-0.469^{***}	-0.471^{***}
	(0.008)	(0.032)	(0.009)	(0.010)	(0.033)	(0.011)	(0.037)	(0.037)

N	22,802	21,879	22,085	18,634	21,711	18,059	17,854	17,730
Log Likelihood	-15,777.5	-14,248.2	-15,154.2	-12,866.7	-14,113.2	-12,366.7	-11,644.4	-11,545.7
Akaike Inf. Crit.	31,559.1	28,512.4	30,320.4	25,741.3	28,248.4	24,749.4	23,308.9	23,117.49
Note:								** p<0.1; **p<0.05; ***p<0.01*

When I distinguish between manual and non manual work as the treatments, the picture starts to depict something else at work, suggesting that non manual gig workers are indeed the primary driver of higher political interest. In Table 8, non-manual gig workers are considerably more likely to report high political interest, even when controlling for socioeconomic factors, precarious work, or social inclusion variables. There is some effect for manual gig workers when socioeconomic variables are controlled, but this effect more or less disappears across other specifications.

Similarly, those who rely on gig work report lower rates of political interest than casual gig workers across different specifications, although the difference is less pronounced (see Table 9). Though none of these models support H1, there appears to be mounting evidence for something similar to H3.1 and H3.2. Instead of depressing political interest in an absolute sense, manual gig work and reliance on gig work predicts lower political interest compared to non manual and casual gig workers.

Table 8. Maximum Likelihood Estimates of Political Interest on Gig Work - Manual and Non Manual

	Dependent variable:							
	Political Interest							
	Naive	SE	Pr	Inclusion	Naive	SE	Pr	Inclusion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GW Manual	0.037	0.141	0.003	0.047				
	(0.094)	(0.102)	(0.097)	(0.106)				
GW Non Manual					0.445^{***}	0.368^{***}	0.383^{***}	0.497^{***}
					(0.118)	(0.125)	(0.122)	(0.130)
⥮								
Constant	-0.058^{***}	-0.532^{***}	-0.060^{***}	-0.012	-0.060^{***}	-0.532^{***}	-0.061^{***}	-0.014
	(0.008)	(0.032)	(0.009)	(0.010)	(0.008)	(0.032)	(0.009)	(0.010)
N	22,802	21,879	22,085	18,634	22,802	21,879	22,085	18,634
Log Likelihood	-15,781.2	-14,251.5	-15,156.3	-12,870.6	-15,774.0	-14,248.0	-15,151.2	-12,863.2
Akaike Inf. Crit.	31,566.5	28,519.1	30,324.6	25,749.3	31,552.0	28,512.1	30,314.5	25,734.5
Note:								** p<0.1; **p<0.05; ***p<0.01*

⥮ Model coefficients for under 26, sex, education, children, second job, self-emp, financial diff, income, can't vote, and migrant status not reported in table. Refer to Table 7 or Table 2 for the covariate groups for each model type. For full model output for the table above, see Appendix, Table S4.

Table 9. Maximum Likelihood Estimates of Political Interest on Gig Work - Rely and Casual

	Dependent variable:							
	Political Interest							
	Naive	SE	Pr	Inclusion	Naive	SE	Pr	Inclusion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GW Rely	0.207*	0.195*	0.142	0.137				
	(0.108)	(0.117)	(0.112)	(0.122)				
GW Casual					0.202*	0.269**	0.168	0.330***
					(0.103)	(0.111)	(0.106)	(0.116)
⥮								
Constant	-0.059***	-0.532***	-0.060***	-0.012	-0.059***	-0.532***	-0.060***	-0.013
	(0.008)	(0.032)	(0.009)	(0.010)	(0.008)	(0.032)	(0.009)	(0.010)
N	22,802	21,879	22,085	18,634	22,802	21,879	22,085	18,634
Log Likelihood	-15,779.5	-14,251.0	-15,155.4	-12,870.1	-15,779.4	-14,249.540	-15,155.0	-12,866.7
Akaike Inf. Crit.	31,562.99	28,518.19	30,322.98	25,748.31	31,562.81	28,515.07	30,322.09	25,741.39
Note:								** p<0.1; **p<0.05; ***p<0.01*

⥮ Model coefficients for under 26, sex, education, children, second job, self-emp, financial diff, income, can't vote, and migrant status not reported in table. Refer to Table 7 or Table 2 for the covariate groups for each model type. For full model output for the table above, see Appendix, Table S4.

4.4 Voting

Now to turn to the second political outcome: voter turnout. As a reminder, these models rely on some imputed data on voting, and bear in mind the aforementioned bias in turnout reporting (Selb & Munzert, 2013). Further, since migrant status is a significant predictor of missing voter turnout (see Appendix: Table S6), I would like to be careful in interpreting model output that includes migrant status as a covariate, as it could induce collider bias.

With those caveats out of the way, let's first take a look at the naive estimates of voting on gig work and categories in Table 10. Here, we start to see a similar pattern emerging as with political interest: on average, non manual gig workers appear to vote more, and manual gig workers appear to vote less, than the control group.

Table 10. Naive Maximum Likelihood Estimates of Voting on Gig Work

	Dependent variable:				
	Voted				
	(1)	(2)	(3)	(4)	(5)
Gig work - all	-0.092				
	(0.083)				
Non-manual gig work		0.565***			
		(0.173)			
Manual gig work			-0.343***		
			(0.098)		
Rely on gig work				-0.103	
				(0.117)	
Casual gig work					-0.081
					(0.116)
Constant	0.992***	0.989***	0.994***	0.991***	0.991***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
N	27,458	27,458	27,458	27,458	27,458
Log Likelihood	-12,112.75	-12,107.04	-12,107.42	-12,112.98	-12,113.12
Akaike Inf. Crit.	25,983.580	25,974.110	25,969.170	25,985.050	25,985.050
Note:					** p<0.1; **p<0.05; ***p<0.01*1
					Respondents ineligible to vote filtered out, n = 1095.

Table 11 looks at all gig workers and their propensity for voting, starting with the naive model, then introducing each set of controls in turn (Models 2-3), before combining them in Model 4. Having established that there is higher political interest among gig workers, driven mostly by non manual gig workers, I include political interest as a covariate to see if significant estimates on voting emerge if political interest is first controlled for, in models 5-9. Political interest likely acts as a mechanism, so controlling it can help identify the controlled direct effect when the individual does or does not have political interest (Cinelli et al., 2020). In the final model, I also included migrant status, though note that by adding this and political interest, this reduces the sample by nearly 10,000 observations.

Without controlling for political interest, gig work overall seems to have no discernible impact on voting, though it looks like there could be some effect when controlling for precarious work variables (not significant). However, if I control for political interest and precarious work (Model 7), a small, significant estimate appears. Overall though, it seems like the relationship between gig work generally and voting is inconclusive; in almost all specifications, the MLEs for gig work are small and insignificant.

Table 11. Maximum Likelihood Estimates of Voting on Gig Work

	Dependent variable:								
	Voted								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Naive	SE	Pr	Comb.	Naive + PI	SE + PI	Pr + PI	Comb. + PI	+ Mig.
Gig work	-0.092	-0.028	-0.139	-0.037	-0.161	-0.075	-0.179*	-0.072	-0.032
		(0.083)	(0.091)	(0.087)	(0.093)	(0.099)	(0.107)	(0.103)	(0.117)
Political Interest					0.929***	0.845***	0.910***	0.841***	0.842***
					(0.024)	(0.025)	(0.024)	(0.025)	(0.027)
Migrant Status									-0.130***
									0.035
⥮									
Constant	0.992***	0.858***	1.030***	0.866***	0.604***	0.630***	0.643***	0.642***	0.629***
	(0.009)	(0.009)	(0.031)	(0.010)	(0.031)	(0.013)	(0.037)	(0.014)	(0.042)
N	27,312	26,833	27,026	26,742	20,554	19,959	20,156	19,880	17,006
Log Likelihood	-12,112.	-10,680.	-11,589.	-10,565.	-8,539.4	-7,773.1	-8,218.8	-7,697.7	-6,700.33
Akaike Inf. Crit.	24,229	21,377	23,190	21,153	17,084	15,564	16,451	15,419	13,426.67

Note: ** p<0.1; **p<0.05; ***p<0.01*

Respondents ineligible to vote filtered out, n = 1095.

⥮ Model coefficients for under 26, sex, education, children, second job, self-emp, financial diff, and income not reported in table. Refer to Table 2 for the covariate groups for each model type. For full model output for the table above, see Appendix, Table S6.

Now to turn to the categorizations of gig work, which seem to have varying effects based on the naive models. For the sake of simplicity and to maximize on my sample, I will stick to reporting models with socioeconomic and precarious controls, rather than including political interest and migrant status, both of which are problematic in terms of missingness.[7] Table 12 reports the coefficients for each gig work category, and here again we see the pattern emerge as with political interest: non manual workers have higher predicted likelihood to vote, manual workers are less likely to vote, and reliance vs casual gig work is in the direction we expect, but the coefficients are small and insignificant.

Table 12. Maximum Likelihood Estimates of Voting on Gig Work, by Category

	Dependent variable:			
	Voted			
	(1)	(2)	(3)	(4)
Non manual gig work	0.572***			
	(0.198)			
Manual gig work		-0.230**		
		(0.108)		
Rely on gig work			-0.100	
			(0.129)	
Casual gig work				0.028
				(0.132)
⥮				
Constant	0.867***	0.866***	0.866***	0.866***
	(0.031)	(0.031)	(0.031)	(0.031)
N	26,742	26,742	26,742	26,742
Log Likelihood	-10,560.790	-10,563.470	-10,565.360	-10,565.630
Akaike Inf. Crit.	21,143.580	21,148.940	21,152.720	21,153.260
Note:				**p<0.1; **p<0.05; ***p<0.0*

Respondents ineligible to vote filtered out, n = 1095

⥮ Model coefficients for under 26, sex, education, children, second job, self-emp, financial diff, and income not reported in table. For full model output for the table above, see Appendix, Table S8.

What does this mean in probabilistic terms? As discussed earlier, Probit coefficient interpretation can be somewhat opaque, so Table 13 presents the probability changes in voting likelihood for the naive models and the models controlling for socioeconomic and

[7] For transparency, I provide a full model specification with political interest and migrant status added as covariates in the Appendix, Table S12. The estimates change in magnitude, but not in direction, and manual work becomes insignificant. There is a tradeoff in using the fully-specified model though: 111 gig workers are dropped due to missingness in political interest (n=77) and migrant status (n=50), which are sizable losses to withstand for adding covariates, given the starting point of 397 gig workers.

precarious variables, calculated using R's generic predict function (R Core Team, 2020). Here, it is much easier to observe and compare the estimated changes in probability across the different gig work categories. Of note is the 11.8 percentage point *increase* in the probability for non manual gig workers vs non gig workers, compared to the 6.8 point *decrease* for manual gig workers. This further underlines the importance of distinguishing between types of work completed when considering political outcomes: here we see that manual gig workers are drastically less likely to vote than non manual workers.

Table 13. Marginal probability changes of voting, naive and controlled model estimates

		Prob Δ (Gig work - Non gig work)				
		All	Non Manual	Manual	Casual	Rely
Model Types	Naive	-0.023	+0.101	-0.098	-0.020	-0.026
	With controls	-0.010	+0.118	-0.068	+0.008	-0.0287

4.5 Robustness Checks

4.5.1 Propensity Score Matching

Though the Probit models attempt to address this through the inclusion of controls, selection bias into gig work could certainly remain an issue. I have already identified multiple variables where gig workers are different from non gig workers at baseline (for example in age, gender, migrant status), making it difficult to isolate the impact of gig work on its own. To address this, I follow the lead of Emmenegger and colleagues (2017) in their paper on unemployment and political interest among the young and Cirillo and colleagues (2021) in their working paper on gig work and economic insecurity in Italy, and use Propensity Score Matching as a robustness check. First, gig workers are matched with non gig workers on certain important covariates, using a propensity score calculated for each individual on entering into gig work, and then matching gig workers and non gig workers based on their propensity scores. Second, the matched dataset is used in a Probit regression model predicting voter turnout and political interest on gig work.[8] The results are displayed in Table 14, first considering all gig workers, then the four categories of gig work.

The results are (somewhat) encouraging in terms of corroborating my main analysis. Almost all the coefficients are in the directions we expect: non manual gig workers have higher likelihoods of reporting political interest and voting than their matched controls, and

[8] I chose covariates to match on based on two considerations: their size of and significance of the difference of means between gig and non gig workers, and their relative measured importance in predicting political interest and voting. Since matching on many covariates leads to the "curse of dimensionality" and potentially dropping many observations due to lack of common support, I needed to be thrifty in my selection process (Cunningham, 2022).

manual gig workers and those reliant on gig work are less likely to vote. Unfortunately there is considerable uncertainty based on this matched sample, and few estimates are considered significant. It is possible that a matching process with fewer covariates and fewer observations getting taken off common support would produce smaller standard errors, but that comes with the risk of lower quality matches. Future investigations using PSM as an identification strategy will likely benefit from a larger N of sampled gig workers.

Table 14. Maximum Likelihood Estimates using Matched Data

	Dependent variable:									
	Political Interest	Voted	Political Interest	Voted	Political Interest	Voted	Political Interest	Voted	Political Interest	Voted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gig work - all	0.238**	-0.007								
	(0.118)	(0.137)								
Non manual gig			0.392**	0.423*						
			(0.174)	(0.235)						
Manual gig					0.165	-0.153				
					(0.147)	(0.154)				
Rely on gig work							0.256	-0.157		
							(0.168)	(0.186)		
Casual gig work									0.200	0.042
									(0.157)	(0.176)
Constant	-0.052	0.916***	-0.000	1.126***	-0.135	0.832***	-0.050	1.068***	-0.033	0.900***
	(0.090)	(0.110)	(0.127)	(0.159)	(0.110)	(0.117)	(0.125)	(0.142)	(0.117)	(0.130)
N	464	492	216	232	298	333	229	268	258	281
Log Likelihood	-318.502	-232.590	-144.140	-68.818	-205.755	-178.367	-156.934	-119.314	-177.527	-131.550
Akaike Inf. Crit.	641.003	469.181	292.279	141.636	415.510	360.734	317.867	242.627	359.054	267.100

Note: ** p<0.1; **p<0.05; ***p<0.01*

Voting matched on gender, having child/ren, age, and financial difficulty.

Political interest matched on gender, education, age, and having a second job.

4.5.2 Limiting control group to employed individuals

As a final robustness check, I filtered out control individuals who reported not being employed (though as discussed in section 3.3.1, some gig workers identified as not employed; these were kept in the dataset). The results can be found in the Appendix, Tables S9-S11. Though there are small differences in estimates, I do not see anything that significantly challenges my findings using the full sample.

5. Discussion

Taking stock, my findings align with my expectations that gig work would depress political turnout, but run contrary to my expectations that gig work would also depress political interest. This is an interesting finding on its own. Consider manual gig workers: if gig work does not depress their political interest (Table 8), but it does depress voter turnout (Table 12), what is the mechanism behind the gig work-voter turnout connection? Is it simply a lack of opportunity to vote, or is it more due to a lack of faith in voting itself? There is some evidence that those who engaged in self-employment most similar to gig work—atypical, autonomous employment without employees—leads to greater support for "new-left" parties and redistribution policies (Jansen, 2019), but there are also suggestions that this kind of atypical work instead leads to a general distrust of political elites and less motivation to vote (Standing, 2011).

Another suggestion is that gig work can enhance feelings of solidarity among workers facing similar conditions (the "voice" as discussed by Kalleberg, 2018). Montgomery and Baglioni (2020) discuss the "gig economy strike" which took place across UK cities in 2018, which brought together gig workers and gig work-adjacent workers such as fast food workers in common cause. Worker solidarity could explain the heightened political interest, without necessarily implying higher voter turnout, as the political interest is channeled into other forms of political expression such as protest.

Finally, the dimensions of migrant labor and skilled/unskilled labor remain important to consider, particularly with respect to the limits of political empowerment. Vandaele (2020) observes that since gig work often has lower barriers to entry, especially with respect to language and documentation requirements, this incentivizes migrants to take on gig work over conventional employment in order to support themselves. This presents a host of potential issues, as migrant workers may be less aware of their labor rights (making them easier to exploit) and as gig work often lacks important social protections, this potentially exacerbates workers' outsider status. Thus, there is potential for segmentation even within platform work, with more high-skill and/or non migrant workers organizing for improved working conditions and using their political voice, and migrant and/or low-skill workers increasingly exposed to unsafe or unfair labor practices.

5.1 Limitations

There are several limitations to this study, across the following categories: measurement, cross-sectional data, and available data.

First, measurement. As O'Farrell and Montagnier (2020) discuss in depth, attempts at measuring gig work have often come up short, and there is no reason to think that the UKLS is not subject to the same issues. The 397 gig workers represent around 1% of the total sample, likely an underrepresentation of the real proportion in the population. If those 397 are a representative sample of gig workers, this does not necessarily present major issues for my study; if they are not, however, my results could very well be biased.

Second, this study analyzes cross-sectional data. It is much more difficult to ascribe causal effects to gig work when I cannot observe outcomes before and after an individual takes part in gig work. Though I attempt to minimize selection bias as much as possible using sets of controls and a robustness check using PSM, I cannot say with certainty that I succeeded. As seen, the gig workers in my sample are substantially different from the general sample, which makes identifying valid controls a challenge.

Third, though the UKLS is a high quality panel study, there are drawbacks in this particular wave. As discussed in Section 3.3.2, there are high levels of missingness in my political outcome variables. Further, Wave 11 does not include questions on participation in unions or civic organizations, nor does it include other types of political participation, such as attending a demonstration. This limits the opportunity to observe how political interest among gig workers might express itself in other ways beyond voting. Finally, it is difficult to ascertain working hours and work schedules from the data, and thus this study does not consider how free time and socialization might connect gig work and voting.

5.2 Further research

There are numerous opportunities for further research from here. First, if the UKLS continues to include gig work questions in future waves, this will present exciting opportunities for using time-series data to understand how gig work might produce variation in political interest and participation in individuals over time. Second, since the UK has a very specific labor and political context, future studies should consider other countries with different political systems and approaches to social welfare. Third, the observation of higher political interest among gig workers merits further investigation; this could be due to an unobserved confounder, or perhaps there is a causal link here. Fourth, the categorizations of gig work should be investigated further. As I admitted in section 3.3.1, the categories I present are somewhat arbitrary, and reflect the availability and distribution of data in my sample. Future investigations into gig economy work will benefit from a rigorous exploration of the varieties of gig work and the firming up of typologies. Finally, gig work likely affects different sub-populations differently, and thus investigations into heterogeneous effects are worthwhile (as a starting point, I provide two heterogeneous effects plots in Appendix: Figures S1-S2).

6. Conclusion

This thesis makes three unique contributions to the literature: first, I find significant quantitative evidence that makes the case for differentiating among gig worker types, especially along the lines of manual and non manual labor. Second, to my knowledge this is the first quantitative study that attempts to connect gig work explicitly with political outcomes, and the findings are compelling, including an almost 7 percentage-point decrease in estimated likelihood of voting for manual gig workers. This underlines the importance of understanding the platform economy as a driver of political inequalities. Finally third, I find that gig workers do not lack political interest: on the contrary, they report as-high or higher political interest than non gig workers. Thus, while the platform economy may exacerbate political inequalities in terms of voting, perhaps this is more due to diminished interest in voting itself, rather than a lack of interest in politics generally. This could spell problems in the future for traditional electoral politics, especially if work arrangements continue to grow more casual and precarious for many.

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8. References: Data analysis

All analysis was coded in R using RStudio. All code written can be found in this GitHub repository: https://github.com/jellingwood-ftw/MPP-Thesis, however note that per UKLS's data agreement, I am unable to share the dataset publicly. All R packages used are credited below.

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Appendix

Table S1. Balance Table of Mean Differences between Gig Workers and Non Gig Workers

Variable	Control (Non Gig Work)	Treat (Gig Work)	P value
sex (1 = M)	0.444	0.594	0.000
age	50.355	40.463	0.000
Edu level	2.923	2.591	0.000
Have child/ren	0.233	0.320	0.000
Number of children	0.405	0.602	0.000
St HH Income	-0.001	0.093	0.068
Second Job	0.045	0.230	0.000
Self-employed	0.073	0.342	0.000
Financial Difficulty	0.072	0.152	0.000
Migrant Status	0.159	0.230	0.002
Weekly working hours	36.226	35.297	0.491
Bad health	0.362	0.270	0.000
Urban	0.757	0.766	0.690
Student	0.054	0.124	0.000
Political Interest	0.476	0.558	0.006
Can't vote	0.037	0.075	0.009
Support redistributive taxation (/10)	6.384	5.994	0.024
Support Brexit party (/10)	2.280	2.094	0.321

Table S2. Maximum Likelihood Estimates for Selection into Gig Work - Excluding Migrant Status

	Dependent variable:				
	All	Casual (<20hrs)	Rely (>=20hrs)	Non-Manual	Manual
	(1)	(2)	(3)	(4)	(5)
Sex (1 = M)	0.210***	0.130**	0.262***	0.146**	0.231***
	(0.044)	(0.055)	(0.061)	(0.061)	(0.053)
Under age 26	0.459***	0.539***	0.191**	0.376***	0.467***
	(0.058)	(0.067)	(0.093)	(0.083)	(0.067)
High school eqv	0.103	0.123	0.064	0.405*	0.037
	(0.100)	(0.129)	(0.136)	(0.232)	(0.106)
Higher degree	0.185*	0.191	0.155	0.699***	-0.074
	(0.102)	(0.131)	(0.137)	(0.231)	(0.110)
Has child/ren	0.154***	0.104	0.172***	0.012	0.218***
	(0.051)	(0.066)	(0.065)	(0.072)	(0.060)
St. HH Income	-0.013	-0.022	0.001	-0.004	-0.015
	(0.021)	(0.027)	(0.028)	(0.028)	(0.026)
Second Job	0.691***	0.753***	0.447***	0.680***	0.554***
	(0.061)	(0.071)	(0.089)	(0.077)	(0.077)
Self-emp	0.775***	0.404***	0.926***	0.810***	0.654***
	(0.052)	(0.076)	(0.063)	(0.068)	(0.064)
Financial diff	0.303***	0.225***	0.324***	0.303***	0.257***
	(0.067)	(0.087)	(0.088)	(0.094)	(0.080)
Constant	-2.846***	-2.993***	-3.131***	-3.507***	-2.882***
	(0.100)	(0.128)	(0.137)	(0.232)	(0.107)
N	30,147	30,147	30,147	30,147	30,147
Log Likelihood	-1,752.783	-1,067.341	-909.052	-862.696	-1,178.183
Akaike Inf. Crit.	3,525.565	2,154.682	1,838.104	1,745.392	2,376.366
Note:					*p<0.1; **p<0.05; ***p<0.01

Table S3. Marginal probability changes of political interest on gig work

	Model Specifications				
	Naive	SE	Pr	Inc.	All Covars
Prob Δ (gig work - non gig work)	+0.081	+0.086	+0.063	+0.095	+0.093

Table S4. Maximum Likelihood Estimates of Political Interest on Gig Work - Manual and Non Manual

	Dependent variable:							
	Political Interest							
	Naive	SE	Pr	Inclusion	Naive	SE	Pr	Inclusion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GW Manual	0.037	0.141	0.003	0.047				
	(0.094)	(0.102)	(0.097)	(0.106)				
GW Non Manual					0.445^{***}	0.368^{***}	0.383^{***}	0.497^{***}
					(0.118)	(0.125)	(0.122)	(0.130)
Under age 26		-0.350^{***}				-0.351^{***}		
		(0.027)				(0.027)		
Sex (1 = M)		0.379^{***}				0.378^{***}		
		(0.018)				(0.018)		
High school eqv		0.251^{***}				0.250^{***}		
		(0.034)				(0.034)		
Higher degree		0.729^{***}				0.726^{***}		
		(0.035)				(0.035)		
Has child/ren		-0.326^{***}				-0.326^{***}		
		(0.021)				(0.021)		
Second job			0.210^{***}				0.202^{***}	
			(0.041)				(0.041)	
Self-emp			0.183^{***}				0.176^{***}	
			(0.032)				(0.032)	
Financial Diff			-0.224^{***}				-0.225^{***}	
			(0.034)				(0.034)	

St HH Income		0.063***	0.096***			0.063***	0.097***	
		(0.009)	(0.009)			(0.009)	(0.009)	
Can't vote				-0.243***				-0.245***
				(0.045)				(0.045)
Migrant status				-0.135***				-0.135***
				(0.025)				(0.025)
Constant	-0.058***	-0.532***	-0.060***	-0.012	-0.060***	-0.532***	-0.061***	-0.014
	(0.008)	(0.032)	(0.009)	(0.010)	(0.008)	(0.032)	(0.009)	(0.010)
N	22,802	21,879	22,085	18,634	22,802	21,879	22,085	18,634
Log Likelihood	-15,781.2	-14,251.5	-15,156.3	-12,870.6	-15,774.0	-14,248.0	-15,151.2	-12,863.2
Akaike Inf. Crit.	31,566.5	28,519.1	30,324.6	25,749.3	31,552.0	28,512.1	30,314.5	25,734.5

Note: * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table S5. Maximum Likelihood Estimates of Political Interest on Gig Work - Rely and Casual

	Dependent variable:							
	Political Interest							
	Naive	SE	Pr	Inclusion	Naive	SE	Pr	Inclusion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GW Rely	0.207*	0.195*	0.142	0.137				
	(0.108)	(0.117)	(0.112)	(0.122)				
GW Casual					0.202*	0.269**	0.168	0.330***
					(0.103)	(0.111)	(0.106)	(0.116)
Under 26		-0.349***				-0.352***		
		(0.027)				(0.027)		
Sex (1 = M)		0.378***				0.379***		
		(0.018)				(0.018)		
High school eqv		0.251***				0.251***		
		(0.034)				(0.034)		
Higher degree		0.728***				0.728***		
		(0.035)				(0.035)		
Has child/ren		-0.326***				-0.326***		
		(0.021)				(0.021)		
Second job			0.208***				0.205***	
			(0.040)				(0.041)	
Self-emp			0.179***				0.182***	
			(0.032)				(0.032)	
Financial Diff			-0.225***				-0.225***	
			(0.034)				(0.034)	
St HH Income		0.063***	0.096***			0.063***	0.096***	
		(0.009)	(0.009)			(0.009)	(0.009)	
Can't vote				-0.243***				-0.246***
				(0.045)				(0.045)

Migrant status				-0.136^{***}				-0.135^{***}
				(0.025)				(0.025)
Constant	-0.059^{***}	-0.532^{***}	-0.060^{***}	-0.012	-0.059^{***}	-0.532^{***}	-0.060^{***}	-0.013
	(0.008)	(0.032)	(0.009)	(0.010)	(0.008)	(0.032)	(0.009)	(0.010)
N	22,802	21,879	22,085	18,634	22,802	21,879	22,085	18,634
Log Likelihood	-15,779.5	-14,251.0	-15,155.4	-12,870.1	-15,779.4	-14,249.540	-15,155.0	-12,866.7
Akaike Inf. Crit.	31,562.99	28,518.19	30,322.98	25,748.31	31,562.81	28,515.07	30,322.09	25,741.39

Note: * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table S6. Probit Regression predicting missing voter turnout across study variables

	Dependent variable:			
	Missing Voter Turnout, 2019			
	(1)	(2)	(3)	(4)
Gig work	-0.010	0.074	0.065	0.137*
	(0.070)	(0.073)	(0.074)	(0.081)
Age		0.005***	0.005***	0.002***
		(0.0005)	(0.0005)	(0.001)
Sex (1 = M)		-0.005	0.0003	0.009
		(0.015)	(0.016)	(0.017)
High school eqv		0.019	0.016	-0.047
		(0.029)	(0.030)	(0.034)
Higher degree		-0.012	-0.017	-0.016
		(0.030)	(0.030)	(0.035)
Has child/ren		0.017	0.021	0.013
		(0.019)	(0.019)	(0.021)
Second job			0.090**	0.066
			(0.037)	(0.041)
Self-emp			-0.059**	-0.059*
			(0.029)	(0.033)
Financial Diff			0.024	0.065*
			(0.031)	(0.035)
St HH Income		-0.015*	-0.014*	-0.021**
		(0.008)	(0.008)	(0.009)
Migrant Status				-0.372***
				(0.026)
Constant	0.018**	-0.237***	-0.242***	-0.216***
	(0.008)	(0.042)	(0.042)	(0.047)
N	27,902	26,914	26,742	21,613
Log Likelihood	-19,337.430	-18,571.690	-18,448.270	-14,627.040
Akaike Inf. Crit.	38,678.860	37,159.380	36,918.550	29,278.080
Note:				** p<0.1; **p<0.05; ***p<0.0*

Table S7. Maximum Likelihood Estimates of Voting on Gig Work - Full model output

	Dependent variable:								
	Voted								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Naive	SE	Pr	Comb.	Naive + PI	SE + PI	Pr + PI	Comb. + PI	+ Mig.
Gig work	-0.092	-0.028	-0.139	-0.037	-0.161	-0.075	-0.179*	-0.072	-0.032
	(0.083)	(0.091)	(0.087)	(0.093)	(0.099)	(0.107)	(0.103)	(0.109)	(0.117)
Under 26		-0.717***		-0.715***		-0.586***		-0.584***	-0.553***
		(0.031)		(0.031)		(0.035)		(0.036)	(0.037)
Sex (1 = M)		-0.024		-0.017		-0.127***		-0.120***	-0.117***
		(0.020)		(0.020)		(0.023)		(0.024)	(0.025)
High school eqv		0.181***		0.180***		0.093**		0.091**	0.088**
		(0.032)		(0.032)		(0.039)		(0.039)	(0.043)
Higher degree		0.794***		0.787***		0.521***		0.516***	0.494***
		(0.035)		(0.035)		(0.042)		(0.042)	(0.046)
Has child/ren		-0.463***		-0.448***		-0.326***		-0.315***	-0.264***
		(0.023)		(0.023)		(0.027)		(0.027)	(0.029)
Second job			0.432***	0.395***			0.335***	0.306***	0.265***
			(0.055)	(0.059)			(0.065)	(0.067)	(0.070)
Self-emp			0.019	-0.022			-0.052	-0.055	-0.036
			(0.036)	(0.038)			(0.042)	(0.044)	(0.048)
Financial Diff			-0.361***	-0.301***			-0.290***	-0.257***	-0.244***
			(0.033)	(0.034)			(0.040)	(0.041)	(0.044)
St HH Income		0.195***	0.193***	0.180***		0.162***	0.150***	0.150***	0.138***
		(0.012)	(0.011)	(0.012)		(0.014)	(0.013)	(0.014)	(0.015)
Political Interest					0.929***	0.845***	0.910***	0.841***	0.842***
					(0.024)	(0.025)	(0.024)	(0.025)	(0.027)

Migrant Status									-0.130***
									(0.035)
Constant	0.992***	0.858***	1.030***	0.866***	0.604***	0.630***	0.643***	0.642***	0.629***
	(0.009)	(0.031)	(0.010)	(0.031)	(0.013)	(0.037)	(0.014)	(0.038)	(0.042)
N	27,458	26,833	27,026	26,742	20,554	19,959	20,156	19,880	17,006
Log Likelihood	-12,112.75	-10,680.960	-11,589.050	-10,565.580	-8,539.488	-7,773.168	-8,218.815	-7,697.797	-6,700.334
Akaike Inf. Crit.	24,229.50	21,377.93	23,190.11	21,153.150	17,084.9	15,564.34	16,451.63	15,419.59	13,426.67
Note:									** p<0.1; **p<0.05; ***p<0.0*

Respondents ineligible to vote filtered out, n = 1095.

Table S8. Maximum Likelihood Estimates of Voting on Gig Work, by Category - Full model output

	Dependent variable:			
	Voted			
	(1)	(2)	(3)	(4)
Non manual gig work	0.572***			
	(0.198)			
Manual gig work		-0.230**		
		(0.108)		
Rely on gig work			-0.100	
			(0.129)	
Casual gig work				0.028
				(0.132)
Under 26	-0.719***	-0.714***	-0.715***	-0.716***
	(0.031)	(0.031)	(0.031)	(0.031)
Sex (1 = M)	-0.018	-0.016	-0.017	-0.017
	(0.020)	(0.020)	(0.020)	(0.020)
High school eqv	0.180***	0.180***	0.180***	0.180***
	(0.032)	(0.032)	(0.032)	(0.032)
Higher degree	0.785***	0.786***	0.787***	0.787***
	(0.035)	(0.035)	(0.035)	(0.035)
Has child/ren	-0.449***	-0.448***	-0.448***	-0.449***
	(0.023)	(0.023)	(0.023)	(0.023)
Second job	0.388***	0.399***	0.395***	0.393***
	(0.059)	(0.059)	(0.059)	(0.059)
Self-emp	-0.031	-0.017	-0.020	-0.024
	(0.038)	(0.038)	(0.038)	(0.038)
Financial Diff	-0.303***	-0.300***	-0.301***	-0.301***
	(0.034)	(0.034)	(0.034)	(0.034)
St HH Income	0.181***	0.181***	0.180***	0.180***
	(0.012)	(0.012)	(0.012)	(0.012)

Constant	0.867***	0.866***	0.866***	0.866***
	(0.031)	(0.031)	(0.031)	(0.031)
N	26,742	26,742	26,742	26,742
Log Likelihood	-10,560.790	-10,563.470	-10,565.360	-10,565.630
Akaike Inf. Crit.	21,143.580	21,148.940	21,152.720	21,153.260
Note:				**p<0.1; **p<0.05; ***p<0.0*

Respondents ineligible to vote filtered out, n = 1095.

Figure S1. Heterogeneous effects on political interest and voting across different covariates - All gig work

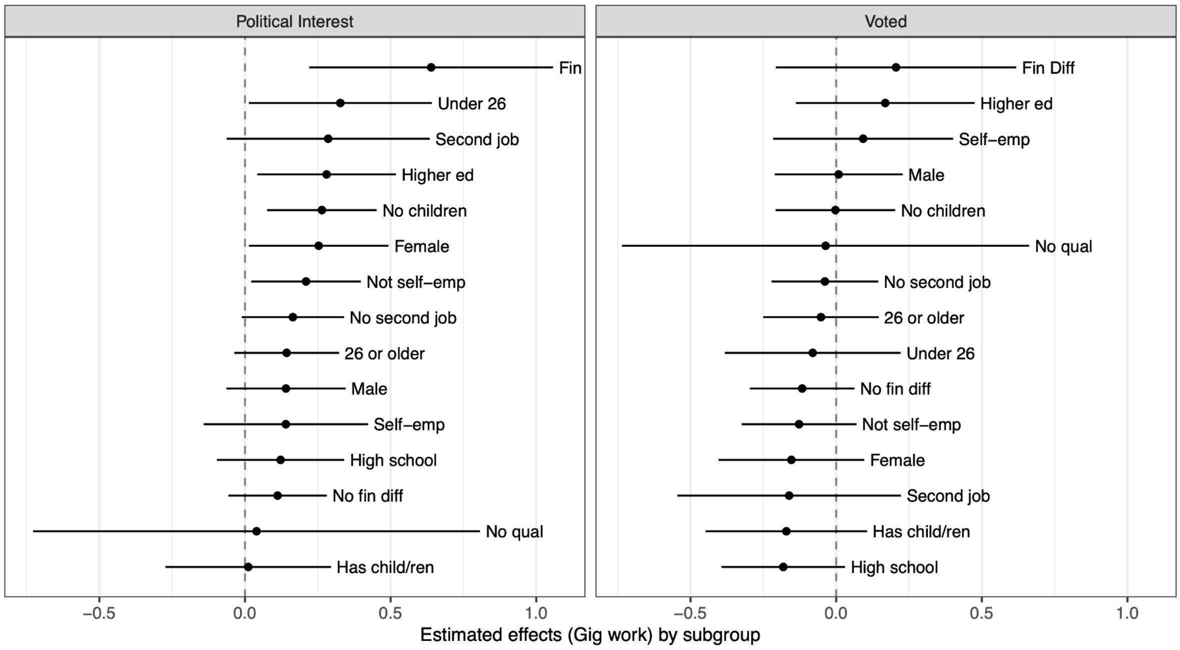

Figure S2. Heterogeneous effects on political interest and voting across different covariates - Manual gig work

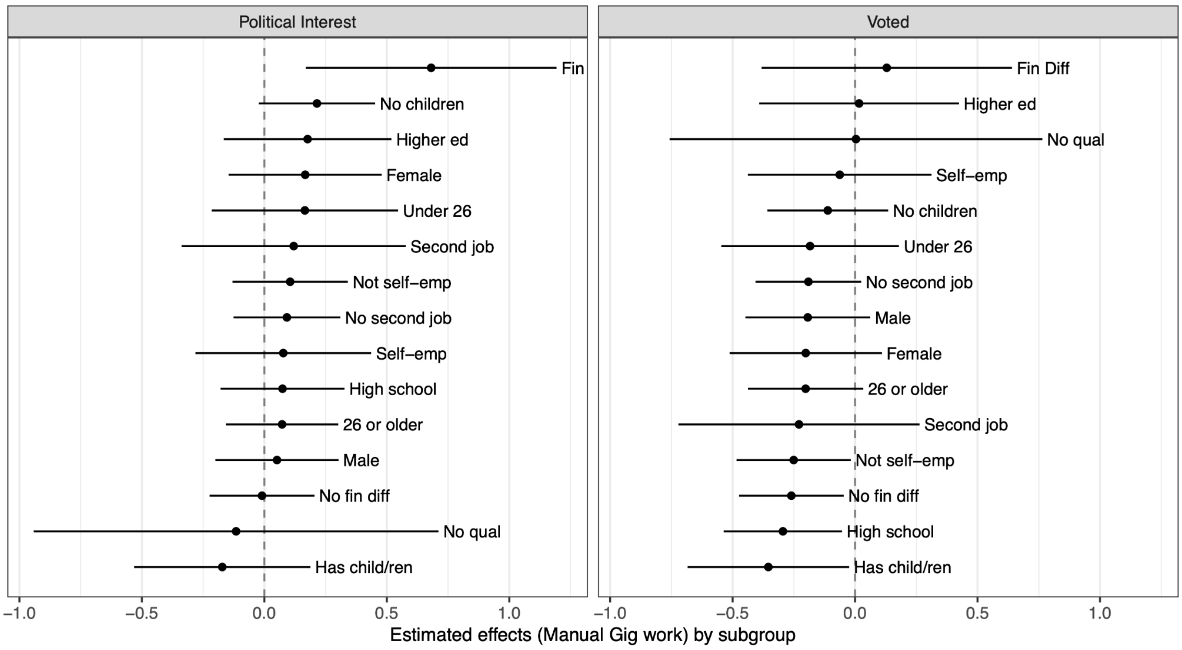

Table S9. Maximum Likelihood Estimates for Selection into Gig Work - Employed Subgroup

	Dependent variable:		
	Gig Work		
	(1)	(2)	(3)
Sex (1 = M)	0.215***		0.187***
	(0.048)		(0.052)
Under age 26	0.448***		0.556***
	(0.062)		(0.066)
High school eqv	-0.289**		-0.201
	(0.128)		(0.136)
Higher degree	-0.256**		-0.190
	(0.128)		(0.136)
Has child/ren	0.060		0.054
	(0.054)		(0.058)
St. HH Income	-0.087***		-0.064**
	(0.026)		(0.026)
Second Job	0.205***		0.179***
	(0.062)		(0.066)
Self-emp		0.644***	0.603***
		(0.060)	(0.071)
Financial diff		0.638***	0.684***
		(0.051)	(0.060)
Migrant status		0.421***	0.392***
		(0.069)	(0.080)
Constant	-1.974***	-2.251***	-2.292***
	(0.129)	(0.028)	(0.140)
N	14,042	17,642	13,935
Log Likelihood	-1,459.788	-1,737.697	-1,341.450
Akaike Inf. Crit.	2,935.575	3,483.395	2,704.899
Note:			** p<0.1; **p<0.05; ***p<0.01*

Table S10. Maximum Likelihood Estimates of Political Interest on Gig Work - Employed Subgroup

	Dependent variable:							
	Political Interest							
	Naive	SE	Pr	Inclusion	SE + Pr.	Pr. + Inc.	SE + Inc.	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gig work	0.243***	0.341***	0.197**	0.269***	0.273***	0.216**	0.362***	0.299***
	(0.075)	(0.082)	(0.078)	(0.085)	(0.083)	(0.088)	(0.092)	(0.093)
Age		0.012***			0.012***		0.012***	0.012***
		(0.001)			(0.001)		(0.001)	(0.001)
Sex (1 = M)		0.405***			0.405***		0.395***	0.392***
		(0.023)			(0.024)		(0.026)	(0.026)
High school eqv		0.364***			0.370***		0.332***	0.345***
		(0.082)			(0.082)		(0.092)	(0.094)
Higher degree		0.904***			0.904***		0.867***	0.874***
		(0.082)			(0.083)		(0.093)	(0.094)
Has child/ren		-0.059**			-0.058**		-0.036	-0.038
		(0.025)			(0.025)		(0.027)	(0.028)
Second job			0.259***		0.258***	0.228***		0.219***
			(0.046)		(0.047)	(0.051)		(0.052)
Self-emp			0.289***		0.161***	0.300***		0.178***
			(0.036)		(0.038)	(0.040)		(0.042)
Financial Diff			-0.036		-0.018	-0.040		-0.025
			(0.048)		(0.049)	(0.053)		(0.055)
St HH Income		0.086***	0.141***		0.086***	0.141***	0.085***	0.086***
		(0.012)	(0.011)		(0.012)	(0.012)	(0.013)	(0.013)
Can't vote				-0.224***		-0.216***	0.040	0.024
				(0.070)		(0.072)	(0.077)	(0.078)
Migrant status				-0.048		-0.043	-0.116***	-0.109***

				(0.034)		(0.035)	(0.037)	(0.037)
Constant	-0.097***	-1.457***	-0.178***	-0.068***	-1.465***	-0.149***	-1.400***	-1.410***
	(0.011)	(0.094)	(0.013)	(0.014)	(0.095)	(0.015)	(0.106)	(0.107)
N	12,916	12,437	12,541	10,532	12,367	10,238	10,131	10,083
Log Likelihood	-8,912.95	-8,004.15	-8,525.27	-7,267.89	-7,932.91	-6,960.17	-6,535.42	-6,485.47
Akaike Inf. Crit.	17,829.9	16,024.3	17,062.5	14,543.7	15,887.8	13,936.3	13,090.8	12,996.9
Note:								* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table S11. Maximum Likelihood Estimates of Voting on Gig Work - Employed Subgroup

	Dependent variable:							
	Voted							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gig work	-0.080	0.043	-0.103	-0.004	-0.175*	-0.045	-0.170*	-0.066
	(0.083)	(0.092)	(0.087)	(0.094)	(0.099)	(0.108)	(0.103)	(0.110)
Age		0.022***		0.022***		0.017***		0.017***
		(0.001)		(0.001)		(0.001)		(0.001)
Sex (1 = M)		-0.051*		-0.048*		-0.165***		-0.161***
		(0.026)		(0.026)		(0.031)		(0.031)
High school eqv		0.157**		0.153**		0.033		0.023
		(0.076)		(0.077)		(0.090)		(0.091)
Higher degree		0.852***		0.843***		0.523***		0.510***
		(0.078)		(0.079)		(0.092)		(0.093)
Has child/ren		-0.063**		-0.059**		-0.046		-0.046
		(0.027)		(0.027)		(0.032)		(0.032)
Second job			0.380***	0.337***			0.319***	0.277***
			(0.058)	(0.062)			(0.070)	(0.073)
Self-emp			0.168***	0.075*			0.047	0.008
			(0.041)	(0.044)			(0.049)	(0.051)
Financial Diff			-0.102**	-0.077			-0.081	-0.076
			(0.049)	(0.051)			(0.059)	(0.061)
St HH Income		0.215***	0.249***	0.211***		0.175***	0.191***	0.170***
		(0.015)	(0.014)	(0.016)		(0.018)	(0.017)	(0.018)
Political Interest					0.922***	0.813***	0.888***	0.809***
					(0.032)	(0.034)	(0.032)	(0.034)
Constant	0.980***	-0.406***	0.912***	-0.409***	0.620***	-0.236**	0.584***	-0.227**
	(0.012)	(0.092)	(0.014)	(0.092)	(0.017)	(0.108)	(0.019)	(0.110)

N	15,627	15,316	15,396	15,269	11,719	11,423	11,508	11,383
Log Likelihood	-6,971.638	-6,043.459	-6,647.702	-6,001.614	-4,897.510	-4,432.211	-4,715.302	-4,404.143
Akaike Inf. Crit.	13,947.280	12,102.920	13,307.400	12,025.230	9,801.020	8,882.423	9,444.605	8,832.286
Note:	** p<0.1; **p<0.05; ***p<0.01*							
	Respondents ineligible to vote filtered out, n = 1095.							

Table S12. Maximum Likelihood Estimates of Voting across GW Categories: including political interest and migrant status as controls

	Dependent variable:			
	Voted			
	(1)	(2)	(3)	(4)
Non manual gig work	0.385*			
	(0.222)			
Manual gig work		-0.154		
		(0.139)		
Rely on gig work			-0.053	
			(0.165)	
Casual gig work				-0.011
				(0.163)
Under 26	-0.556***	-0.552***	-0.553***	-0.553***
	(0.037)	(0.037)	(0.037)	(0.037)
Sex (1 = M)	-0.117***	-0.117***	-0.117***	-0.117***
	(0.025)	(0.025)	(0.025)	(0.025)
High school eqv	0.088**	0.089**	0.088**	0.088**
	(0.043)	(0.043)	(0.043)	(0.043)
Higher degree	0.493***	0.494***	0.494***	0.494***
	(0.046)	(0.046)	(0.046)	(0.046)
Has child/ren	-0.265***	-0.263***	-0.264***	-0.264***
	(0.029)	(0.029)	(0.029)	(0.029)
Second job	0.261***	0.266***	0.264***	0.264***
	(0.070)	(0.070)	(0.070)	(0.070)
Self-emp	-0.042	-0.033	-0.036	-0.037
	(0.047)	(0.048)	(0.048)	(0.047)
Financial Diff	-0.244***	-0.243***	-0.244***	-0.244***
	(0.044)	(0.044)	(0.044)	(0.044)
St HH Income	0.138***	0.138***	0.138***	0.138***
	(0.015)	(0.015)	(0.015)	(0.015)

Pol int	0.841***	0.842***	0.842***	0.842***
	(0.027)	(0.027)	(0.027)	(0.027)
Migrant Status	-0.129***	-0.128***	-0.129***	-0.130***
	(0.035)	(0.035)	(0.035)	(0.035)
Constant	0.629***	0.629***	0.629***	0.629***
	(0.042)	(0.042)	(0.042)	(0.042)
Observations	17,006	17,006	17,006	17,006
Log Likelihood	-6,698.743	-6,699.767	-6,700.320	-6,700.368
Akaike Inf. Crit.	13,423.490	13,425.530	13,426.640	13,426.740
Note:				** p<0.1; **p<0.05; ***p<0.0*

Respondents ineligible to vote filtered out, n = 1095.

Statement of Authorship

I hereby confirm and certify that this master thesis is my own work. All ideas and language of others are acknowledged in the text. All references and verbatim extracts are properly quoted and all other sources of information are specifically and clearly designated. I confirm that the digital copy of the master thesis that I submitted on 7 May 2022 is identical to the printed version I submitted to the Examination Office on 9 May 2022.

DATE: 7 May 2022

NAME: Julia Ellingwood

SIGNATURE: