Worker Welfare in the Gig Economy

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Abstract

Many workers provide short-term labor services through intermediaries: gig work. It is hard to quantify how much individuals benefit from these arrangements because of their novelty, and the fact they comprise a part-time activity for some and a full-time occupation for others. This paper estimates a model of gig work participation using data on the UK's food delivery market to study the surplus that workers receive. The average surplus is £1,000 per month but some are worse off because of misperceptions that cause suboptimal entry. Policies targeting full-time participants, such as California's Proposition 22, likely fail to benefit workers overall.

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1 Introduction

There has been widespread and rapid growth in the number of self-employed workers offering short-term labor services to customers via digital platforms (Garin et al., 2023; Datta et al., 2023). Through the lens of revealed preference, the vast take up of this type of work—gig work—suggests that individuals are benefiting significantly. However, this observation is at odds with qualitative evidence that many workers have negative experiences of the gig economy (Dubal, 2019; Ravenelle, 2019).

In light of a desire to better protect workers in the gig economy with new regulation (Goldman and Weil, 2021; Harris and Krueger, 2015), a comprehensive understanding of the gig work surplus is of first-order importance for policymakers. However, little is known about the size of this surplus and the impact of changes to the gig work environment. For example, what are the welfare effects of mandating platforms to offer benefits to full-time workers, or of reducing participation costs?

Understanding the worker surplus from the gig economy is particularly difficult because it entails an unusual bundle of amenities. For example, it offers flexible hours but also uncertain pay (Angrist et al., 2021). Koustas (2019) also shows that individuals tend to enter the gig economy after a deterioration in their financial circumstances, which indicates that gig work occurs at a specific point in the life cycle. These factors make a like-for-like comparison with an outside option hard.

A further difficulty stems from the different role gig work plays in people's lives. It is a full-time job for some but a secondary source of income for others. Consequently, in a world without the gig economy, some workers would switch to a traditional full-time job while others may completely reshuffle their selection of daily activities alongside any intensive margin adjustments. Such highly non-linear responses pose a challenge for empirical analyses (Reiss and Wolak, 2007).

This paper tackles these issues and estimates the distribution of the worker surplus for a typical gig economy in the UK. I introduce new administrative and survey data, evince novel patterns in behavior, and bring these contributions together with a structural model of gig work participation. The framework uses workers' endogenous exit decisions, which arise because of learning about misperceptions over the value of gig work, to infer heterogeneous outside options.

The results imply a large surplus on average with the typical gig worker receiving £1,000 in monthly surplus. Yet, misperceptions about the value of gig work cause one in six participants to be left worse off; this finding is consistent with many workers' negative experiences of gig work. Individuals who participate less than 25% full-time generate the majority of the total surplus. This leads to a trade-off between ensuring protections for full-time gig workers and maintaining the appeal of gig work to most participants when platforms reduce earnings in response to new costs.

The ideal experiment to identify a worker's surplus from participating in the gig economy would require offering the individual amounts of money which, if accepted, prevents them from working in the gig economy. The amount at which the individual is indifferent between accepting and rejecting the offer equals the worker's surplus. Absent this experiment, it is desirable to infer the surplus from observable behavior.

This paper estimates the population's joint distribution of valuations of gig work and outside options. Crucially, the difference between these two variables equals the gig work surplus. I do this for motorcycle drivers in the UK's food delivery market, which makes up one-fifth of the UK's gig economy (Cornick et al., 2018). The industry exhibits features characteristic of gig work more generally, such as per-job payments and flexible hours. From hereon, "gig economy" will generally refer to this market.

For the estimation, I use administrative data from a vehicle insurer (the "firm"), which has two attractive features. First, the firm provides *mandatory* insurance to workers in this gig labor market, which can be purchased with either an hourly or monthly policy premium. The insurance, which primarily covers damage to third parties while working, is essentially a necessary participation cost and poses gig workers with a choice between a fixed or variable cost structure. Second, the data tracks workers across different platforms, which ensures a complete view of workers' engagement with the gig economy (Caldwell and Oehlsen, 2021).

Workers' choices over a fixed or variable premium contain information about their expected hours in the gig economy because high-hours participants would save money on a fixed policy, and *vice versa*. Contrasting policy choice with realized hours in the data reveals that one-quarter of workers make non-cost-minimizing decisions. This could be due to either *ex ante* misperceptions of future hours or *ex post* shocks that affect hours after the policy choice has been made.

If *ex post* shocks are responsible for non-cost-minimization, then dynamic behavior would be uncorrelated with cost-minimization because these shocks should be randomly allocated across gig workers and independent of any individual characteristics that drive dynamic patterns in behavior. Instead—and consistent with workers having *ex ante* misperceptions—dynamic behavior is correlated with cost-minimization. Optimistic individuals (*i.e.*, those who do not work enough to justify their fixed policy choice) reduce their hours after they enter, and exit faster. Conversely, pessimistic workers (*i.e.*, those who work too much to account for their variable policy choice) increase their hours initially and exit at a slower rate.

Intuitively, if valuations of gig work determine hours in the gig economy, then misperceptions of hours reveal misperceptions of valuations. In this context, the dynamic patterns of participation and engagement in the gig economy also provide evidence of learning. Optimistic individuals enter the gig economy in anticipation of high value but, in learning that this is not the case, reduce their hours and exit faster, while the opposite is true for pessimists who increase their hours and exit slower.

New survey evidence also corroborates this narrative. Participants report that their expectations of gig work do not match their experiences. This is especially true for negative components of the job, such as vehicle running costs. In addition, self-reports of misperceptions correlate with non-cost-minimization; workers who select the fixed policy but end up working few hours are the most likely to report that the amenities of gig work are worse than expected.

The combination of misperceptions and learning offers a way to identify heterogeneous outside options. When a worker endogenously exits because of learning, their perceived valuations just before and after they exit bound their outside option. Equipped with this logic, the task is to estimate workers' money metric valuations of gig work, their misperceptions, and the learning process. This exercise requires empirical variation that is germane to individuals' misperceptions. Observing individual-level (non-)cost-minimization allows for partitioning workers in a way that is informative of misperceptions and, thus, satisfies this requirement.

To operationalize these insights, I build a model of participation in the gig economy inspired by the literature on usage goods (Nevo et al., 2016). Reflecting key patterns in the data, the framework allows for heterogeneity in three areas: outside options and valuations can vary across workers, and workers differ in their misperceptions of their valuations. Workers decide to participate in the gig economy if their perceived valuation exceeds their outside option. Upon entering, they select either a fixed or variable insurance policy based on their expected hours, which are driven by their perceived valuation. Then, workers learn about their true valuation through experience and adjust their behavior in turn. Workers exit if their perceived value falls below their outside option, or if they receive an exogenous shock. A rich set of data moments identifies the model which I estimate by simulated method of moments.

This structural approach is attractive because of the highly non-linear environment that workers face, which renders reduced-form approaches less useful. For instance, imagine obtaining an estimate of a worker's reservation wage while they are a participant in the gig economy. Comparing this with their earnings to construct a reduced-form measure of the surplus does not account for the fact that if a worker leaves the gig economy, then their reservation wage will change as the individual reoptimizes their daily activities. Therefore, although this strategy may be suitable for some exercises, such as valuing flexible work (Chen et al., 2019), workers' utility outside the gig economy is the relevant benchmark to measure the gig work surplus.

The results imply a large gig work surplus. The typical participant enjoys a monthly surplus of £1,066 or, equivalently, one-third of the mean employee's monthly earnings in the UK. There is large variation (SD £1,775) with some workers extracting thousands of pounds of surplus from gig work, while others are on the margin of participating. The analysis implies workers enjoy 70% to 80% of their hourly wage as a surplus. Over half of the total surplus is generated by workers who work less than 60 hours per month in the gig economy because the vast majority of individuals do so. Still, high-hours individuals receive a higher surplus on average.

Several factors could explain the substantial gig work surplus. Most gig workers are in the bottom half of the income distribution and they often receive negative income shocks before entering (Bernhardt et al., 2022; Koustas, 2019), which suggests a high marginal utility of income. Workers who especially value gig work amenities are more likely to participate. Further, participants' outside options may be low due to underemployment (Lachowska et al., 2023), and gig work's flexibility allows it to fit around other high-value activities, which raises the surplus.

There is a trade-off between ensuring benefits for full-time gig workers and maintaining gig work's appeal to all participants, which stems from the concentration of the aggregate surplus at the low end of the hours' distribution. If regulators compel platforms to offer benefits to high-hours individuals,[1] then this will impose costs on these firms. Some of these costs will be passed on to workers as lower wages. All participants will likely be affected because platforms cannot *a priori* distinguish who will qualify for benefits and multi-homing across platforms undermines any targeted incidence. The lower wages that follow the policy impact the surplus and participation of low-hours workers, who create the majority of the surplus, the most.

A counterfactual policy evaluation of California's Proposition 22 health insurance

[1] This can be through new legislation or clarifications around the legal tests that are used to define employment status. See efforts along these lines in, for example, the US, Europe, and India.

stipend crystallizes this point. Precisely, I study the introduction of mandatory benefits for workers who reach hours thresholds in the gig economy. This policy reduces worker welfare if even 40% of the cost is borne by workers through an hourly wage penalty; this threshold is half the estimated pass-through rates of mandated employer-sponsored health insurance (Kolstad and Kowalski, 2016).

Lastly, I use the model to consider the role of participation costs and misperceptions in determining the gig work surplus. As an example of the former, I study the introduction of the variable insurance policy, which lowered fixed costs and increased welfare by 4.7% mainly through higher participation. Concerning the latter, misperceptions cause an allocative inefficiency that stifles the gig work surplus. Pessimistic workers who would receive a positive surplus do not participate, and optimistic participants may lose out compared to their outside option. Absent misperceptions the gig work surplus is 21% higher, which stems equally from both channels. Misperceptions and the exits they cause are congruent with negative qualitative evidence about gig work and the high degree of churn amongst gig workers.

The paper proceeds as follows: section 2 discusses institutional details and the data; section 3 presents a series of reduced form facts, which motivate the model in section 4; section 5 explains the estimation; section 6 discusses the results and counterfactuals; and, finally, section 7 concludes.

2 Empirical Setting

This section describes institutional details about the empirical setting, the data available, and the sample for the analysis. I study self-employed workers who deliver food by motorcycle to customers via digital platforms in the UK. The data comes from a firm that provides mandatory insurance to workers in this market and collects administrative data from many different platforms. I complement this information with a survey of workers' experiences in the gig economy.

2.1 Institutional Details

Some of the most visible forms of gig work involve moving passengers and goods on the road. Toyota Prii with smartphones fixed on dashboards and motorcycles adorned with insulated food delivery boxes are now quintessential sights for many cities around the world.[2] Indeed, Cornick et al. (2018) find that this makes up over half of gig work in the UK.

In this sense, I focus on a representative part of the gig economy: food delivery. Specifically, self-employed workers who deliver food by motorcycle to customers on behalf of digital platforms are the subject of this paper. These individuals are free to onboard and pick their hours and location. They are paid by the job, which leads to uncertain wages because of fluctuating demand and supply, as well as other factors (*e.g.*, traffic and waits at restaurants). Gig workers are entitled to few employment rights beyond health and safety and discrimination protections. For example, they do not receive sick pay and are not guaranteed a minimum wage.

An accepted job requires the worker to drive to a restaurant, pick up a meal, and then deliver the meal to the customer. Platforms differ in the ways that they provide information and offer compensation. For example, some platforms tell workers where the customer is located before the acceptance of a job, while others only disclose the location of the restaurant. Compensation often adjusts to the distance of a job but this is done coarsely. Some platforms also provide other financial incentives, such as a bonus for making a set amount of deliveries within a month.

Crucially, individuals working on UK roads *must* have an enhanced level of vehicle insurance called Hire and Reward (H&R) insurance. This is a necessity for many gig workers, including food delivery workers. The insurance covers damage to third parties while working and further coverage can be purchased to protect one's own vehicle under certain circumstances (*e.g.*, fire and theft). This insurance does not cover the food being delivered, which is dealt with by the intermediary platform.

From the perspective of a gig worker, this insurance is an unavoidable cost to be minimized. The H&R market offers insurance in two forms: variable and fixed. Variable policies are paid approximately by the hour, while the fixed policies insure workers for 30 days and are paid for upfront. From a cost-minimization perspective, the fixed policy is preferable if a worker anticipates working many hours over the next month. Aside from their financial implications, both policies are very similar in terms of how they are marketed and paid for. Further, although the policies have different implications for the variance of income, quantitatively the insurance value of the variable policy is small, as described in appendix A.

[2] Prii is the plural of Prius, see Toyota's press release.

2.2 Data

The data for this paper comes from a H&R insurer that offers both the variable and fixed policies to gig workers. The firm receives data from different intermediary platforms to facilitate its insurance policies and, therefore, does not suffer from individuals selecting or switching between work providers. Further, the firm provides the full menu of policies available on the H&R market so it is reasonable to assume there is little selection of workers into the firm who are seeking a particular policy. The raw observations are at the job level and contain information about the length of jobs, when they took place, a unique worker identifier, the age and gender of the worker, the type of insurance policy, and the premium. The main omission from the data is worker compensation.

Given the choice environment that workers face *vis-á-vis* a 30-day policy and the aim of estimating a holistic gig work surplus, I aggregate the data from the job level to the worker-month level to construct, for example, a monthly hours worked variable.[3] The monthly data also has the advantage that it reduces the influence of high-frequency shocks that affect workers' labor supply decisions. I treat a worker's first appearance in the dataset as their first entrance into the gig economy. While workers may have already undertaken gig work, the rarity of policy switchers within the firm's data suggests that switching across firms is not a significant problem. Similarly, I define exit from the gig economy as a worker not reappearing in the data.

The data spans January 2018 to October 2021. I restrict to worker months observed from the start of 2019 and onward because the insurer was growing rapidly in 2018 and did not offer a consistent menu of policies. This period includes the Covid-19 pandemic which, unlike many industries, was a period of continuity and even growth for the food delivery market. In appendix C, I show that the reduced form evidence is consistent both before and during the pandemic.

Some workers have multiple spells in the gig economy. For these workers, I keep their first spell, where a spell is defined as working consecutive months with a break of no longer than three months. The fixed policy can offer additional forms of coverage to a worker's vehicle for a higher premium, while the variable policy provides only third-party coverage. To adjust for this, I use reports of willingness to pay for additional coverage from the survey (discussed below) to correct workers' premiums.

[3] Thus, the measure of labor supply is the sum of time spent on food deliveries over a month. Workers often spend 20 to 30% of their time idle between jobs, which I account for in the structural estimation by appropriately adjusting a labor supply elasticity used as an empirical moment.

Further detail on this adjustment and other filters used to prepare the data can be found in appendix B.

Switching is not an important margin of response for workers. For every 100 gig workers who exit, only seven switch policies, which is unsurprising given the literature on inertia in household finance decision making (Farrell and Klemperer, 2007). Therefore, I remove switchers from the analysis to abstract from this rare decision. Further, many policy switches take place at the start of a second stint in the gig economy, in which case the first spell is kept in the sample. Lastly, individuals can also opt for an annual policy but this is taken up by less than a fifth of individuals for whom it is difficult to evaluate whether policy choices are cost-minimizing, hence, I omit them from the sample.

The firm also has quote data, which contains the menu of prices that workers face when they make their participation and policy decisions. This is useful for two reasons. Firstly, it reveals the distribution of fixed policy premiums faced by the population without any selection. I leverage the observed selection into policies based on premiums in the estimation. Secondly, it allows for the construction of individual-level "break-even" points. That is, the number of hours at which both the fixed and variable policy entail the same cost. For illustrative purposes, I often calculate an average break-even point as equal to the average observed fixed premium divided by the average hourly premium for third-party policyholders only.

Table 1 presents summary statistics for the sample broken down by the type of policy, where the observations have been collapsed to the worker level. In total, I observe 86,024 worker months. Two-thirds of workers select the variable policy and these workers tend to work less both in terms of hours and the number of jobs that they complete in a month, but they stay in the gig economy longer than their peers on the fixed policy. Hourly premiums for variable policyholders are £0.94 per hour and monthly premiums are roughly ten times this amount on average.

I complement this administrative data with a survey conducted in collaboration with the firm. The survey was sent out in June 2022 to the firm's active customer base who had subscribed to receiving promotional material. The survey contained questions regarding workers' experiences of the gig economy, especially relative to their expectations, and their policy choice. The survey received over 500 responses in total though not all questions were answered by all respondents.

Table 1: Worker-Level Summary Statistics

Statistic	Variable	Fixed	Both
Number of workers	10,589	5,986	16,575
Mean number of jobs	114.19	274.95	172.25
Mean duration (months)	5.42	4.76	5.19
Mean monthly hours	43.76	87.51	59.56
SD monthly hours	38.24	59.98	51.72
Mean monthly premium (£)	–	93.20	–
SD monthly premium (£)	–	41.85	–
Mean hourly premium (£)	0.94	–	–
SD hourly premium (£)	0.31	–	–

Notes: This table shows summary statistics at the worker-level from the analysis sample. The worker-month-level data is collapsed to the worker-level. Then, for example, the mean hours row displays the mean number of hours worked by workers during an average month, and standard deviations are computed across workers. Mean duration is constructed as the average number of months workers spend in the gig economy.

3 Patterns in Gig Work Participation

This section presents four empirical facts about gig work participation. Firstly, there is dramatic variation in the number of hours worked per month across individuals. Secondly, hours worked do not predict survival in the gig economy. Thirdly, workers often do not make cost-minimizing policy choices. Fourthly, cost-minimization is correlated with trends in hours worked and survival.

These facts motivate four features of the model in section 4: (i) workers have different valuations of gig work, which manifest as a distribution of hours worked in the gig economy; (ii) outside options vary across individuals to justify those working few hours remaining in the gig economy; (iii) workers may misperceive their valuations and this can lead to non-cost-minimizing decisions; and (iv) individuals learn about their true valuations over time, which leads to the observed evolution of hours and survival for (non-)cost-minimizing workers.

3.1 Hours Worked

There is enormous dispersion in the number of hours worked in a month by different workers, which suggests that workers are extracting very different value from gig work. Figure 1 illustrates this dispersion and how it relates to policy choice. Panel 1a presents the empirical distribution of hours worked and the share of policies that make up each hours bin, as reflected by the coloring of the bar. There are two key takeaways from this graph. Firstly, two-thirds of workers are on the variable policy. Secondly, most individuals do not work many hours in the gig economy but there is a strong right skew. The modal number of hours worked is approximately 20 hours per month while the mean is 60 hours per month with a standard deviation of 52 hours. Panel 1b reveals a third fact: the distribution of hours looks very different conditional on policy choice. For the variable policy, most of the mass is compact around its mean of 44 hours per month. Conversely, hours are more dispersed under the fixed policy with a mean and standard deviation of 88 and 60 hours per month, respectively.[4]

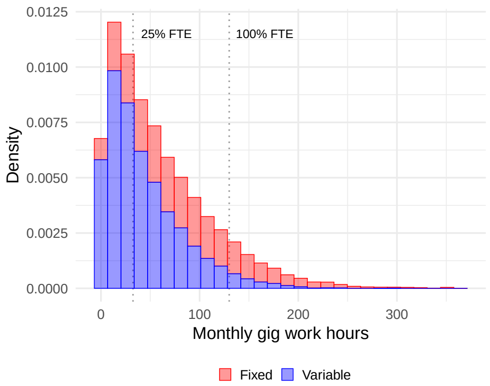
3.2 Policy Choice

With realized hours and premium quotes, it is possible to assess the quality of policy choice from a cost-minimization perspective. To do so, I construct worker-level break-even points, which describe the number of hours above which the fixed policy is most economical. The data is firmly consistent with an intention to cost-minimize but many individuals would be better off on an alternative policy. In section 4, this motivates misperceptions over workers' valuations of gig work, which lead to misperceptions about expected hours and, in turn, non-cost-minimizing policy choices.

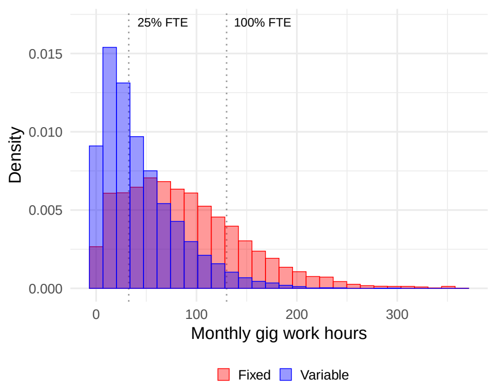
Figure 2 provides a convenient lens through which to view policy choice quality (Handel et al., 2020). The graph shows the share of individuals on the fixed policy for different normalized hours bins. Normalized hours are constructed as hours of work in the gig economy minus an individual's break-even point. A perfect cost-minimizer would exhibit a step function so that when they work below the break-even point, they are always on the variable policy, and when they are above the break-even point,

[4]The firm's quotes data contains information on individuals' age and gender, which can be linked to work hours data. Over 90% of workers in the sample are male, which limits statistical power to discern differences in gig labor supply between genders. Still, regression analysis suggests that women on the variable policy tend to work approximately 4 hours less per month than their male counterparts (p-value 2.4%), while there is no statistically significant difference in hours worked between genders for the fixed policy. Interacting gender with age yields imprecise estimates. In general, hours tend to increase with age regardless of policy although this is more pronounced on the fixed policy where, on average, individuals under 30 work 12 hours less per month than those over 40.

Figure 1: Distribution of Hours Worked



(a) Stacked density by policy choice



(b) Overlapping density by policy choice

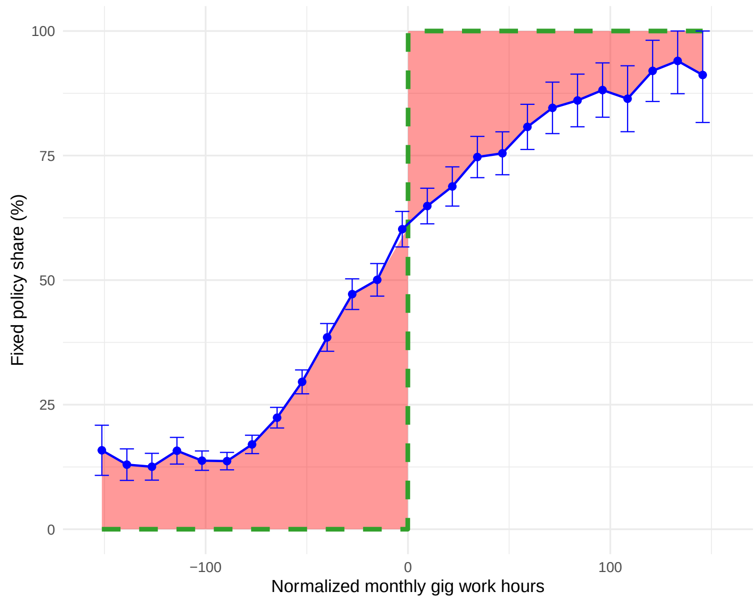
Notes: This figure plots the probability mass of binned hours worked per month for different samples. The sample in panel 1a is all policyholders in the analysis sample and the coloring of the bar is determined by the share of fixed versus variable policy holders. The proportion of the bar that is blue represents the share of workers who are on the variable policy in that hours bin. Two samples are used in panel 1b; the distribution of hours worked by fixed and variable policy holders is shown by the red and blue bars, respectively. The dotted grey lines show where different shares of full-time equivalent (FTE) work fall in the distribution of gig work hours. Each observation in a bin is a worker, where repeated worker observations have been averaged over. For this figure, I have removed individuals with less than three monthly observations in order to reduce the impact of noise, which leaves 9,575 workers.

they are always on the fixed policy. This is illustrated by the dashed green line. At the break-even point, a perfect cost-minimizer would be indifferent between policies. Introducing imperfect foresight would smooth the step function and lead to a monotonically increasing line that crosses the break-even point at 50%.

The data reveals a pattern similar to this, as shown by the blue line in figure 2. Workers far from the break-even point all but minimize their costs and, moving between these extremes, workers have an increasing tendency to opt for the fixed policy. Therefore, the data is strongly supportive of workers trying to minimize costs. But there is still a significant portion of workers who make non-cost-minimizing choices as illustrated by the red shaded regions in figure 2, which highlight deviations from the perfect step function. Further, the blue line crosses the break-even point above the 50% level, which is indicative of optimism from gig workers.

Categorizing workers. For the remainder of this section, I categorize workers based on a combination of their policy choices and whether their choice was cost-minimizing. A worker is defined as cost-minimizing if their policy choice minimized their costs

Figure 2: Fixed Policy Share by Normalized Hours Worked



Notes: This figure plots the share of workers who are on the fixed policy by normalized hours bins. Normalized hours are hours minus an individual's break-even point, which is constructed from the quote data as a worker's quoted or actual monthly premium divided by the analogous hourly premium. Each observation in a bin is a worker, so the hourly bin that an individual falls into is determined by their average monthly hours. The green dashed line indicates the perfect cost-minimizer's policy choice, which is vertical at the break-even point. Standard errors are constructed by applying the law of large numbers to the average of Bernoulli random variables (*i.e.*, $\sqrt{p \cdot (1-p)/N}$ where p is the share of policies on the fixed policy in a bin and N is the number of observations in that bin).

for the majority of months during their tenure in the gig economy.[5] The categories are summarized in table 2 alongside their unconditional share of the population. The colors in the matrix correspond to how these groups are depicted in the figures below. Workers who make cost-minimizing choices are grouped together and referred to as "minimizers", and fixed and variable policy holders who make non-cost-minimizing decisions will be called "optimistic" and "pessimistic", respectively.

Broadly, deviations from cost-minimization could be driven by two factors: firstly, *ex post* shocks that affect workers' hours after they make their policy choice; and, secondly, *ex ante* misperceptions about how much they will work. If *ex post* shocks are responsible for non-cost-minimizing behavior, then these categories should not be

[5]Results are robust to other ways of classifying choice quality. Appendix C replicates the analysis below with alternative categories, where non-cost-minimization is calculated by whether either an individual minimized their total insurance premiums over the course of their spell in the gig economy, or whether they minimized their costs for a typical month.

Table 2: Worker Categories

		Policy Choice: Fixed	Policy Choice: Variable
Cost-Minimizing	Yes	Minimizers 13.1%	Minimizers 59.1%
	No	Optimistic 20.1%	Pessimistic 7.7%

Notes: This table shows the constructions of different worker categories, where the color denote how the categories are shown in subsequent figures. The percentages reflect the proportion of worker-months that fall into each category.

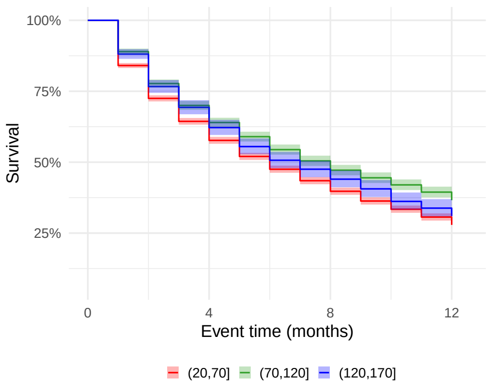
predictive of dynamic behavior in the gig economy. These shocks would be randomly allocated across workers and, thus, independent of worker characteristics that drive dynamic patterns.

3.3 Dynamics of Survival and Hours

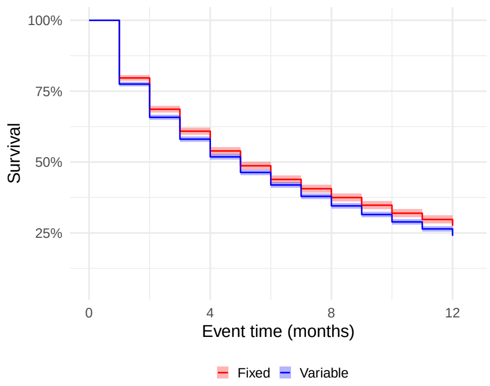
In this subsection, I examine this hypothesis by leveraging repeated observations of gig workers over time to examine dynamic aspects of their behavior and how this correlates with their categories. Figure 3 depicts individuals' survival probabilities over time. Panel 3a shows that hours do not predict survival; grouping workers by the average number of hours they work does not lead to noticeably different survival trajectories and, moreover, any differences are not monotonic in hours. This implies that workers have different outside options since low-hours workers would not remain in the gig economy if they had to sacrifice the same outside option as a full-time gig worker. Further, policy choice is not predictive of survival. Panel 3b shows that fixed and variable policyholders have almost indistinguishable survival paths. Thus, hours and policy choice alone are not informative of tenure in the gig economy.

In contrast, categories strongly predict survival as shown by panel 3c. The optimistic group (*i.e.*, those who select the fixed policy but do not work enough to make it worthwhile) initially exit faster than the other groups; the red line falls below the other two lines in the first period. Conversely, the pessimistic group (*i.e.*, those who select the variable policy but would have saved money on the fixed policy) exit slowest at first, as evinced by the fact the blue line starts above the others. Minimizers' survival probabilities are between these extremes, which reflects their less severe exposure to

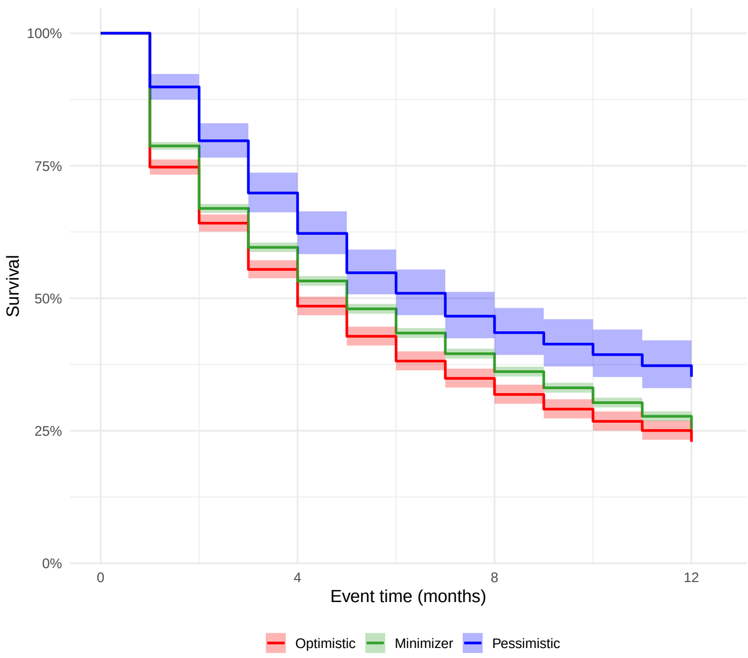
Figure 3: Survival



(a) By hours



(b) By policy



(c) By category

Notes: This figure plots Kaplan-Meier survival curves for different groups in the gig economy. In panel 3a, the green, red, and blue lines denote the hours bins [20, 70), [70, 120), and [120, 170), respectively. Panel 3b shows fixed and variably policyholders in red and blue, respectively. In panel 3c, the green, red, and blue lines denote the minimizers, optimistic, and pessimistic categories, respectively. Event time is tenure month in the gig economy (*i.e.*, $t = 1$ is workers' first month in the gig economy so if an individual does not have a second month in the gig economy, then they exit in the first period).

forces that could push them off the cost-minimizing policy.

This evidence suggests that *ex ante* misperceptions play an important role in non-cost-minimizing policy choices because, if this partitioning of the data only reflected *ex post* shocks, then these dynamic patterns would not be evident. Further, the path of survival points towards learning. Bayesian learning dictates that workers' misperceptions erode quickest early on in their spell when there is a lot to learn and then remain constant after sufficient time has passed. This should manifest in the data as the difference between survival curves appearing early on in workers' spells.

To evince these patterns, I estimate a Cox proportional hazards model with time-varying coefficients.[6] Appendix table C1 displays the estimates which I summarize here. The preferred specification including all controls suggests the optimistic and minimizer categories increase the baseline hazard rate by 48% and 22%, respectively, relative to the pessimistic category over the first two months of a worker's spell in the gig economy. Thereafter, their effects wane. The minimizer category's impact is no longer discernible from zero and the optimistic category's effect falls by two thirds—consistent with learning about misperceptions.

Lastly, I show that categories are also correlated with the evolution of hours worked in figure 4. The figure shows average hours worked in each week of tenure relative to workers' second week in the gig economy to avoid the fact that workers may not begin working at the start of their first week.[7] The different categories display contrasting behavior. Optimistic workers see their hours initially fall while pessimistic workers see their hours increase at the start of their tenure. Cost-minimizing workers also see their hours fall, though less so than optimistic workers, which is in line with the survival evidence for minimizers. Again, this is consistent with the workers experiencing misperceptions and learning.

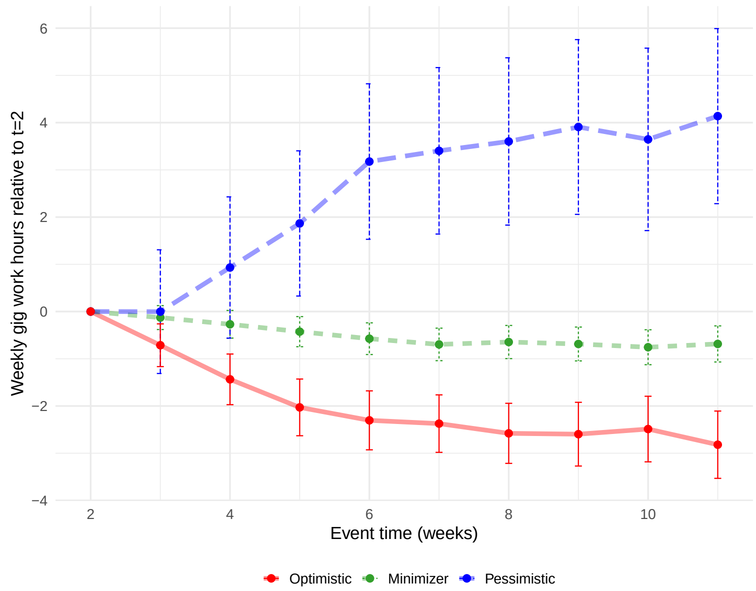
3.4 Survey Evidence

Survey responses from the firm's customers provide strong evidence that expectations of gig work often deviate from reality and that the true value of gig work is learned over time. This data is presented in appendix figures C8 and C9, which I summarize here. Gross earnings expectations are accurate on average, but with significant dispersion

[6] A parametric model also allows for the inclusion of controls although, in appendix C, I show that the visual patterns remain when splitting the sample by age, time periods, and policy coverage. Appendix C also contains a linear probability regression that reveals the same patterns as the Cox proportional hazards model with time varying coefficients.

[7] As with the survival evidence, appendix C shows that the patterns in hours dynamics are robust across different cuts of the data.

Figure 4: Hours Worked Over Time by Category



Notes: This figure plots three sets of coefficients from three separate regressions, which are run on a balanced panel of each category of worker. Weekly hours are regressed on fixed effects and event time dummies, where $t = 2$ corresponds to their second month in the gig economy (*i.e.*, event time is tenure in the gig economy). Intuitively, each coefficient represents the difference in hours at a given point in time from their hours in their first full week in the gig economy. SEs are clustered at the worker level with a HC3 weighting scheme.

such that the majority of workers are left either pleasantly surprised or disappointed in almost equal proportions. Workers report costs and the difficulty of the job to be much higher than expected. Approximately three-quarters of workers found costs to be more than expected, while half of them found the work more difficult than anticipated. Moreover, pessimists are most likely to find gig work better than expected and optimists most frequently report gig work to be worse than expected relative to minimizers. Lastly, around 90% of workers report experiencing learning throughout their tenure in the gig economy.

4 A Theory of Gig Work

In this section, I develop a model of workers' participation in the gig economy analogously to a usaged-based good (Nevo et al., 2016). The model captures the key features of the economic environment as evinced by the reduced form empirics: workers have different valuations, which lead to a distribution of hours worked, but they may misperceive these valuations such that many individuals end up on a more costly policy, while some would be better of outside of the gig economy altogether. In addition, workers learn about their true valuation of gig work over time, which manifests in an evolution of hours worked and survival that is correlated with policy choice and (non-)cost-minimization. The model also allows for workers to experience *ex post* shocks to their valuations and to take temporary breaks from gig work. To aid the exposition, I save most points of discussion until the end.

4.1 The Model

A worker i is endowed with an individual-specific quadruple $\{\theta_i, \nu_i, \phi_i, P_i\} \in \mathbb{R}_+^4$ that contains their true valuation of gig work θ_i, their outside option ν_i, their initial misperception of their valuation ϕ_i, and their fixed policy premium P_i.[8] If the worker enters the gig economy, they decide between the fixed and variable policy $\omega \in \Omega = \{\omega_F, \omega_V\}$ and then, each period, they pick how many hours to work in the gig economy $h \in \mathbb{R}_+$. These choices entail a normative flow utility for worker i of

$$u(h, \omega; \theta_i) = \theta_i \cdot \frac{h^{1-\frac{1}{\varepsilon}}}{1-\frac{1}{\varepsilon}} - \big(p(\omega) + \kappa\big) \cdot h - P_i(\omega),^{9} \tag{1}$$

where $\varepsilon \in (1, +\infty)$ governs the response of hours to the value of gig work and the variable cost of hours. The variable cost is made up of an exogenous linear cost to working $\kappa \in \mathbb{R}_+$ and the hourly insurance premium $p(\omega)$, which equals $p \in \mathbb{R}_+$ if the worker opts for the variable policy ω_V and is zero otherwise. The worker also faces a fixed premium $P_i(\omega)$, which equals P_i if the worker chooses the fixed policy ω_F and is zero otherwise. If the worker decides not to enter the gig economy, then they receive their outside option ν_i every period. Utility and surplus are always measured with the normative utility function described by equation (1).

When the worker is deciding whether to participate, they may misperceive the value of gig work. Formally, before they enter the gig economy, their perceived value of gig work is $\hat{\theta}_{i,0} = \phi_i \cdot \theta_i$. If the worker decides to participate in the gig economy, they will learn about their misperception over time. Concretely, their misperception

[8] Heterogeneity in the fixed premium P_i is motivated by the fact that the firm personalizes prices for the fixed policy but not the variable policy.

[9] Workers' outside options will absorb any intercept in this function.

will erode so that after t periods it is equal to

$$\Phi(t, \phi_i) = \frac{t}{t+\lambda} + \frac{\lambda}{t+\lambda} \cdot \phi_i, \tag{2}$$

where $\lambda \in \mathbb{R}_+$ determines the speed of learning (an increase in λ implies slower learning). This functional form is microfounded by a model of individual-level Bayesian learning (see appendix D). Equation (2) implies that $\lim_{t\to\infty} \Phi(t, \phi_i) = 1$ so the worker will all but perceive their true valuation after sufficient time has passed.

At any point in time, the worker will behave in accordance with their perceived value of gig work $\hat{\theta}_{i,t} = \Phi(t, \phi_i) \cdot \theta_i$, which generates a perceived flow utility for worker i at time t given by

$$u_i(h, \omega; \hat{\theta}_{i,t}) = \hat{\theta}_{i,t} \cdot \frac{h^{1-\frac{1}{\varepsilon}}}{1-\frac{1}{\varepsilon}} - \big(p(\omega) + \kappa\big) \cdot h - P_i(\omega).^{10} \tag{3}$$

Misperceptions can cause individuals to choose non-cost-minimizing policies, and that the opportunity to work in the gig economy can lead to welfare losses when individuals enter because of an inflated valuation that would otherwise fall below their outside option.

Workers may exit the gig economy in any period. This could be due to either endogenous exit, if a worker's perceived value falls below their outside option, or because of an exogenous shock that removes them from the gig economy with probability η. This latter feature captures persistent shocks to valuations or outside options that render the surplus from gig work negative.

Given this series of decisions, the model is solved via backward induction. Exit is either exogenous or equivalent to participation, so I start with hours, then policy choice, and then participation and exit.

Hours worked. Hours are chosen each period by workers conditional on their participation and policy in order to maximize perceived flow utility. Therefore, worker i in period t will pick hours to maximize equation (3), which yields

$$h^*_{i,t}(\omega) = \left(\frac{\hat{\theta}_{i,t}}{p(\omega) + \kappa}\right)^{\varepsilon}.^{11} \tag{4}$$

[10] The subscript i for the utility function $u_i(\bullet)$ captures the role of individual specific fixed policy premiums P_i, which are suppressed as an argument of the function for convenience. This is true also for the value functions $V_i(\bullet)$ and $\tilde{V}_i(\bullet)$ that are defined later.

[11] In the implementation of the model, a time period is set to one month and hours are truncated from above at 480 (=16×30) to reflect time constraints. Workers fully account for this but it rarely bites.

Policy choice. Workers make their policy decision before they have entered into the gig economy and so suffer from their initial misperception. They believe that their flow utility during their tenure in the gig economy will remain constant (*i.e.*, they are naïve about their learning) so they pick whichever contract yields a higher flow utility. Denote the value function

$$V_i\big(\omega; \hat{\theta}_{i,0}\big) = u\big(h_i^*(\omega), \omega; \hat{\theta}_{i,0}\big). \tag{5}$$

Therefore, individuals pick the policy which maximizes their perceived flow utility

$$\omega_i^* = \arg\max_{\omega} \big\{ V_i\big(\omega_F; \hat{\theta}_{i,0}\big), V_i\big(\omega_V; \hat{\theta}_{i,0}\big) \big\}. \tag{6}$$

Participation and exit. Since workers believe they will remain in the gig economy until they exogenously exit, at which point they receive their outside option, they will decide to enter the gig economy if and only if

$$V_i\big(\omega_i^*; \hat{\theta}_{i,0}\big) > \nu_i. \tag{7}$$

Similarly, worker i will exit at time t if their perceptions evolve such that

$$V_i\big(\omega_i^*; \hat{\theta}_{i,t}\big) \leq \nu_i. \tag{8}$$

4.2 Introducing Shocks to the Model

In this subsection, I introduce transitory shocks to workers' valuations of gig work. These *ex post* rationalize fluctuations in hours and temporary exits in the data that are not attributable to learning.

Workers' valuations are subject to independently and identically distributed shocks $\rho_{i,t} \in \mathbb{R}_+$ each period. The distribution of shocks is known to workers and they leave the worker's valuation unchanged in expectation $\mathbb{E}[\rho_{i,t}] = 1$. Thus, on any given period, the worker's true valuation is $\theta_{i,t}^{\rho} = \rho_{i,t} \cdot \theta_i$, although it will be perceived to be $\hat{\theta}_{i,t}^{\rho} = \rho_{i,t} \cdot \Phi(t, \phi_i) \cdot \theta_i$. That is, the worker's normative flow utility is given by

$$u_i(h, \omega; \theta_{i,t}) = \theta_{i,t}^{\rho} \cdot \frac{h^{1-\frac{1}{\varepsilon}}}{1-\frac{1}{\varepsilon}} - \big(p(\omega) + \kappa\big) \cdot h - P_i(\omega), \tag{9}$$

although it is perceived to be

$$u_i(h,\omega;\hat{\theta}_{\rho,i,t}) = \hat{\theta}^{\rho}_{i,t} \cdot \frac{h^{1-\frac{1}{\varepsilon}}}{1-\frac{1}{\varepsilon}} - \big(p(\omega)+\kappa\big) \cdot h - P_i(\omega). \tag{10}$$

If a shock is sufficiently low, then the worker may not want to work in the gig economy. In this case, they can temporarily access their outside option at a discount $\nu_i \cdot (1-\psi)$, where $\psi \in (0,1)$, and work zero hours in the gig economy. I refer to this as temporary exit. Temporary exit reflects two features of reality. Firstly, if an individual participates regularly in the gig economy, they have less time to invest in and raise the value of their outside option. Secondly, it captures any refundable fixed costs to enter into the gig economy.

Conditional on policy choice, gig participants will work if

$$\begin{aligned} u(h^*_{i,t}(\omega),\omega;\hat{\theta}_{\rho,i,t}) &= \frac{1}{\varepsilon-1} \cdot \frac{\big(\hat{\theta}^{\rho}_{i,t}\big)^{\varepsilon}}{\big(p(\omega)+\kappa\big)^{\varepsilon-1}} - P_i(\omega) \leq \nu_i \cdot (1-\psi) \\ \iff \quad \rho_{i,t} &\leq \left(\big(\nu_i \cdot (1-\psi) + P_i(\omega)\big) \Big/ \frac{1}{\varepsilon-1} \cdot \frac{\big(\hat{\theta}_{i,t}\big)^{\varepsilon}}{\big(p(\omega)+\kappa\big)^{\varepsilon-1}}\right)^{\frac{1}{\varepsilon}} = \Gamma(\nu_i,\hat{\theta}_{i,t},P_i). \end{aligned} \tag{11}$$

Therefore, hours worked are determined by

$$h^*_{i,t}(\omega) = \begin{cases} \left(\frac{\hat{\theta}^{\rho}_{i,t}}{p(\omega)+\kappa}\right)^{\varepsilon} & \text{if } \rho_{i,t} > \Gamma(\nu_i,\hat{\theta}_{i,t},P_i), \\ 0 & \text{otherwise.} \end{cases} \tag{12}$$

Workers' participation decisions must incorporate the possibility of temporary exit and engage more fully with the dynamic nature of the problem they face. They discount the future with discount factor $\beta \in (0,1)$ such that they perceive their discounted sum of utility under policy ω for worker i at time t to be

$$\begin{aligned} \tilde{V}_i(\omega;\hat{\theta}_{i,t}) =& \mathbb{E}\left[\sum_{t=0}^{\infty}(\eta\cdot\beta)^t \cdot \max\left\{\frac{1}{\varepsilon-1} \cdot \frac{\big(\hat{\theta}^{\rho}_{i,t}\big)^{\varepsilon}}{\big(p(\omega)+\kappa\big)^{\varepsilon-1}} - P(\omega), \nu_i \cdot (1-\psi)\right\}\right] \dots \\ & \dots + \sum_{t=0}^{\infty}(1-\eta^t)\cdot\beta^t\cdot\nu_i \end{aligned} \tag{13}$$

where the expression makes use of the fact that exogenous exit is an absorbing state.

Therefore, worker i selects policy

$$\omega^*_i = \arg\max_{\omega} \big\{\tilde{V}_i(\omega_F;\hat{\theta}_{i,0}), \tilde{V}_i(\omega_V;\hat{\theta}_{i,0})\big\}, \tag{14}$$

and enters the gig economy if and only if

$$\tilde{V}_i(\omega_i^*; \hat{\theta}_{i,0}) > \frac{\nu_i}{1-\beta}. \tag{15}$$

Exit at a given time t occurs endogenously if and only if

$$\tilde{V}_i\big(\omega_i^*; \hat{\theta}_{i,t}\big) \leq \frac{\nu_i}{1-\beta}. \tag{16}$$

4.3 Discussion

The model describes decisions which are designed to capture the way workers engage with the gig economy. Here I discuss some aspects of the model.

Heterogeneity. The model allows for heterogeneity both across and within workers to reflect the reduced form evidence in the simplest way possible. There is significant variation in hours worked between workers, which motivates individual specific valuations of gig work. Workers make different policy choices; some make cost-minimizing decisions and, for those who do not, there is significant dispersion in how far their hours are from their break-even point. Differences in workers misperceptions of their valuations capture this feature of the data. Further, workers face different outside options that may be correlated with hours and this is critical to their participation in the gig economy. Lastly, workers are subject to transitory shocks that affect their valuation of gig work, as well as permanent shocks that remove them from gig work. These permanent shocks capture persistent negative shocks to the surplus that workers derive from gig work.

Gig work valuations. Workers' valuations of gig work encompass a broad range of factors that determine how gig work affects their utility. The wage is likely an important determinant of valuations but even this is mediated by other factors such as workers' marginal utility of income. Amenities also likely play an important role, for example, flexible hours, absence of a boss, and varying demands of the job. The model allows workers to value these aspects differently but imposes that, conditional on working the same number of hours, workers valuations are equivalent. This does not mean workers with the same number of hours receive the same surplus since they will have different misperceptions and outside options.

Outside options. Outside options constitute workers' welfare in a world where they exogenously do not work in the gig economy. Outside options encapsulate two margins of adjustment. First, they can replace the hours worked in the gig economy with another activity (*e.g.*, leisure or some alternative work). Second, they can adjust the bundle of activities that they undertake in a day. That is, workers can reorganize all the activities in their day and not just the time they would spend in the gig economy.

Misperceptions. Misperceptions manifest visibly as workers not cost-minimizing and as workers promptly reducing their hours and leaving the gig economy. In the model, workers are assume they have perfect knowledge of their valuation. This allows the model to abstract from workers shading their valuations (Smith and Winkler, 2006; Thaler, 1988) and staying in the gig economy to learn about their valuations.

The model also imposes that workers misperceive the value of gig work rather than another parameter in the model. In particular, misperceptions could be about outside options as in Jäger et al. (2022). However, the dynamics of hours and survival in the data, as well as the survey evidence, motivates the choice to embed misperceptions in the value of gig work. In particular, it is hard to conceive how misperceptions in outside options could generate dynamics within the gig economy.

The gig work surplus. Differences in surpluses across workers are driven primarily by variation in gig work valuations and outside options, but they can also differ because of suboptimal labor supply decisions driven by misperceptions. Within workers, shocks to valuations cause the surplus to vary over time and to eventually go to zero because of exogenous exit shocks.

The model's gig work surplus measure does not capture the possibility that outside options could change with, for example, a mass exodus from the gig economy. Plausibly, in the short run, outside options may fall in such a situation as the supply of labor to other markets increases while demand remains unchanged leading to a fall in wages. Thus, the gig work surplus identified here serves as a lower bound.

Learning. The learning process described in equation (2) equals the expected learning by an infinite number of individuals who are subject to a stochastic signal process, as shown in appendix D. In the context of estimation using simulated method of moments, which I outline in section 5, each simulated agent reflects the average of many individuals' Bayesian learning in a stochastic environment. In turn, each simulated agent approximates the behavior of many individuals, and this approximation is more accurate when signals in the learning process are more precise. It is reasonable to believe this applies here because one period is a month, which gives workers significant time to learn about the gig economy. This intuition is supported by the results, which find that learning is fast. The multiplicative nature of learning also implies that the more an individual works in a month, the more they learn in absolute terms about the value of gig work. Lastly, I note that the learning process can approximate learning over many dimensions, as shown in appendix D.

5 Estimation

This section describes the estimation of the model's structural parameters and provides a guide to the identifying variation in the data. Further, I present the parameter estimates and model fit.

5.1 Simulated Method of Moments Estimator

The variable premium p is set equal to its average of £0.94 in the data and I feed the model the empirical distribution of quoted fixed premiums P_i, which can be seen in figure B2. These are the premiums offered by the firm—not necessarily taken by customers—and so do not suffer from selection. Moreover, they are all but uncorrelated with hours worked, which implies they are unrelated to worker valuations θ_i from the perspective of the model. Through conversations with the firm it is also apparent that customers' policies are not priced based on any proxy for misperceptions ϕ_i. Therefore, I assume individuals' fixed premiums are independent of their other characteristics.

To reduce the burden of estimation, I fix the exogenous exit rate η equal to the exit rate of pessimistic workers. In the model, these workers have no reason to leave aside from exogenous shocks. The elasticity parameter ε is mechanically adjusted to ensure an intensive margin labor supply elasticity compatible with empirical evidence. The discount factor β is set to a standard value.

The remaining parameters are estimated using SMM. This requires an assumption about the distribution of heterogeneity in the population. I assume that individuals' valuations θ_i, outside options ν_i, and misperceptions ϕ_i follow a joint log-normal distribution. This has two main advantages. First, it helps to capture the skewed distribution of hours that is evident in the data. Second, it allows for an easily specified pattern of correlations between these individual characteristics.

I impose that misperceptions have a mean of one and are uncorrelated with other worker characteristics. This implies that misperceptions are correct in any subset of the population on average, and corresponds to a benchmark where misperceptions are distributed across the population at random. Practially, it is possible to identify a correlation between misperceptions and valuations but the exact source of identification is unclear and this benchmark fits the data well. In contrast, the zero correlation between misperceptions and outside options is substantively important for the identification of outside options, as I discuss in subsection 5.2. The model still generates correlations between all worker characteristics for participants through selection into the gig economy. In summary, individual heterogeneity is distributed according to

$$\begin{pmatrix} \theta_i \\ \phi_i \\ \nu_i \end{pmatrix} \sim \log \mathcal{N} \left(\begin{bmatrix} \mu_\theta \\ -\sigma_\phi^2/2 \\ \mu_\nu \end{bmatrix}, \underbrace{\begin{bmatrix} \sigma_\theta^2 & 0 & \sigma_{\theta,\nu} \\ 0 & \sigma_\phi^2 & 0 \\ \sigma_{\nu,\theta} & 0 & \sigma_\nu^2 \end{bmatrix}}_{=\Sigma} \right). \tag{17}$$

In practice, I estimate elements of the Cholesky decomposition L of the covariance matrix $\Sigma = LL^T$ in order to ensure the latter is positive semidefinite, where I fix two elements of the lower triangular matrix L to reflect the constraint imposed on the covariance matrix. Further, outside options are censored at £10,000 since the model's parameters are identified from observed participants so the data cannot speak to individuals who are far from entering the gig economy. The idiosyncratic shocks to worker valuations are assumed to be log-normal iid distributed $\rho_{i,t} \sim \log \mathcal{N}(\mu_\rho, \sigma_\rho^2)$ with $\mu_\rho = -\sigma_\rho^2/2$ so that $\mathbb{E}[\rho_{i,t}] = 1$.

This leaves ten parameters to estimate in the model; six parameters describing the joint log-normal distribution, the linear cost to hours κ, the rate at which misperceptions correct λ, the variance of shocks that affect workers valuations σ_ρ^2, and the sunk portion of gig workers' outside options ψ. Let $\boldsymbol{\zeta}$ denote this vector of parameters

$$\boldsymbol{\zeta} = \{\mu_\theta, \sigma_\theta^2, \sigma_\phi^2, \mu_\nu, \sigma_\nu^2, \sigma_{\theta,\nu}, \sigma_\rho^2, \psi, \kappa, \lambda\}.$$

I construct the difference between the jth model moment $\hat{m}_j(\bullet)$ and the jth data moment $m_j(\bullet)$ to be $e_j(\bullet)$ so that

$$e_j(\tilde{X}, X|\boldsymbol{\zeta}) = \hat{m}_j(\tilde{X}|\boldsymbol{\zeta}) - m_j(X),$$

where X denotes the observed data and $\tilde{X}$ denotes the simulated data. The estimated parameters are those that minimize the weighted sum of errors

$$\hat{\boldsymbol{\zeta}} = \arg\min_{\boldsymbol{\zeta}} \ \boldsymbol{e}(\tilde{X}, X|\boldsymbol{\zeta})^T W \boldsymbol{e}(\tilde{X}, X|\boldsymbol{\zeta}),$$

where $\boldsymbol{e}(\bullet)$ is the stacked deviations of the moments $(J \times 1)$ and W is a weight matrix $(J \times J)$.

Standard errors for the parameters are computed according to

$$\hat{\mathbb{V}}(\hat{\boldsymbol{\zeta}}) = \frac{N+1}{N} \cdot \left(\hat{\mathcal{J}}^T W \hat{\mathcal{J}}\right)^{-1} \left(\hat{\mathcal{J}}^T \hat{\Sigma} W \hat{\Sigma}^T \hat{\mathcal{J}}\right) \left(\hat{\mathcal{J}}^T W \hat{\mathcal{J}}\right)^{-1},$$

where N is the number of simulations, $\mathcal{J}$ is the Jacobian matrix of the moment conditions $(J \times K)$, and Σ is the variance-covariance matrix of the moment conditions $(J \times J)$ (Hansen, 1982). The hat notation $\hat{\bullet}$ reflects the fact that these components are functions of the data. In particular, the variance-covariance matrix of the moment conditions is estimated by block bootstrapping at the worker level and recomputing the moments. For moments that do not come from the main dataset, I construct their variances and assume zero correlation with the other moments.

The ten parameters of the model are identified with 23 empirical moments. These moments can be seen in table 5, or a more descriptive list is provided in appendix F. Below, I discuss two empirical moments from the estimation that are external to the administrative data: the labor market share and the labor supply elasticity.

The labor market share is derived from two sources separate to the firm's administrative data. Bertolini et al. (2021) report that 17.1% of the UK workforce work for digital platforms on at least a monthly frequency from a survey of 2,201 workers, and Cornick et al. (2018) state that 21% of the 95 gig workers in their sample work in food delivery. This implies a labor market share of 3.59%.[12] I reconcile the labor market share with the model through a stationarity assumption (*i.e.*, that the employment share of the gig economy is in steady state).

I lean on the labor supply elasticity literature to pin down ε. Given the short-term

[12] I assume independence between these two statistics and use that fact that for two independent random variables X and Y with finite first and second moments $\mathbb{V}(X \cdot Y) = \mathbb{V}(X) \cdot \mathbb{V}(Y) + \mathbb{V}(X) \cdot \mathbb{E}(Y)^2 + \mathbb{E}(X)^2 \cdot \mathbb{V}(Y)$ to construct the covariance matrix of the empirical moments.

nature of gig work for most workers, a Frisch elasticity is most appropriate. Moreover, given these are self-employed workers with total control over their hours one would expect this group of individuals to exhibit a high Frisch elasticity. I take the Frisch elasticity estimate of 0.80 (SE 0.10) from Fisher (2022), which is estimated on a sample of self-employed taxi drivers who are subject to exogenous variation in their wage rates due to London tube strikes. I combine this with earnings estimates for delivery riders and scale this to account for idle time.

In practice, I find the minimum of the objective function using a multi-start simplex search method, the weight matrix is set to normalize the error function to percentage deviations, and I simulate six million workers.

5.2 Sources of Identification

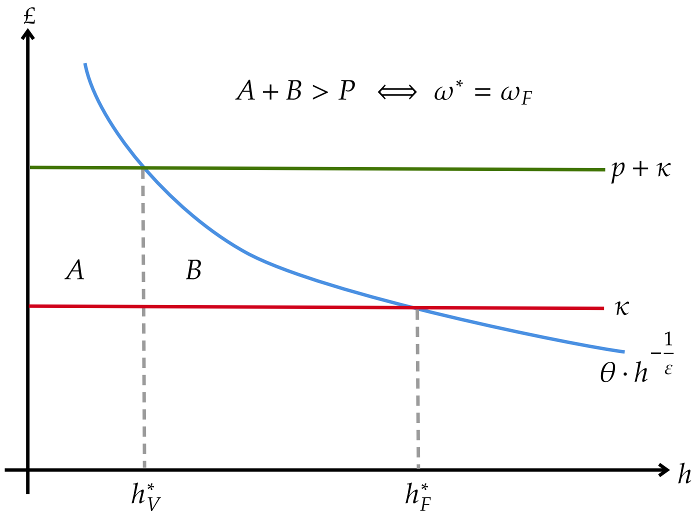
While the parameters are identified from a combination of structural assumptions and moments of the data, it is helpful to consider the particularly close linkages between some parameters and moments. Workers' hours are determined by an unobserved distribution of valuations of gig work $\{\mu_\theta, \sigma^2_\theta\}$. Aside from misperceptions, participants who work the same hours have the same valuations so the gross distribution of valuations is implied by the hours distribution.

The money-metric nature of this valuation comes primarily from the policy choice, which can be framed as the opportunity to buy a higher wage rate at some upfront cost. Figure 5 shows the logic behind this. The additional benefit from switching to the fixed policy is the hourly earnings that are saved rather than paid to the firm (*i.e.*, area A), plus the sum of marginal benefits net of marginal costs for the additional hours that are worked (*i.e.*, area B). Therefore, the linear cost to work κ must imply a solution to this problem that matches the data. To the extent that policy choice pins down a money-metric, variation in fixed premiums P_i also helps identification.

Naturally, the prevalence of non-cost-minimizing choices and a measure of how far these choices were from justifying their policy choice implies the distribution of misperceptions σ^2_ϕ. For example, an individual on the fixed policy who would save money on the variable policy likely overestimated their valuation (*i.e.*, $\phi_i > 1$) but this alone does not provide information about the extent of the individual's over optimism. However, if the individual was only one hour [100 hours] away from the break-even point, then their misperception must have been small [large].

The speed of learning λ is primarily identified from the change in workers' hours

Figure 5: Money-metric Identification



Notes: This illustrates how the model identifies money-metric valuations. The blue curve denotes the marginal benefit of an additional hour in the gig economy, and the red and green lines show the marginal cost under the variable and fixed policy, respectively.

upon entering the gig economy. A greater initial adjustment in hours, for example, indicates a quick rate of learning.

Outside options $\{\mu_\nu, \sigma_\nu^2\}$ are most connected to the employment share of the gig economy and initial hazard rates. Intuitively, the employment share can identify a constant outside option; with a fixed distribution of valuations, a homogeneous outside option can be adjusted to ensure the correct employment share. In addition, the estimation leverages endogenous exit in the model to identify heterogeneity in outside options. With knowledge of the learning process, valuations, and hazard rates, it is possible to infer outside options as the perceived valuations at which optimistic workers decide to leave the gig economy. Crucially, variation in outside options can only be inferred from optimistic workers, so to extrapolate to the population-level requires outside options to be uncorrelated with any other worker characteristics—as in the distributional assumption (17).

The covariance between valuations and outside options $\sigma_{\theta,\nu}$ comes from conditioning the moments on a combination of policy choice and whether the policy choice was cost-minimizing. For example, given knowledge of misperceptions and the speed of learning, differential exit rates amongst variable minimizers and optimistic workers is indicative of outside options. Again, selection into participation plays a key role in mediating the covariance amongst gig workers compared to the population as a whole.

The variance of shocks σ_ρ^2 is identified from the mean within worker standard deviation of hours worked, and the fraction of the outside option that is sunk due to regularly participating in the gig economy ψ is inferred from the prevalence of interruptions to workers' spells in the gig economy (*i.e.*, the fraction of months where workers work zero hours but reappear in the data subsequently).

5.3 Parameters and Model Fit

Table 3 presents the estimates and their associated standard errors in the top panel. The lower panel of the table shows the fixed model parameters. Namely, the variable premium p, the mean and standard deviation of the fixed premium distribution $\{\mu_P, \sigma_P\}$, the discount factor β, exogenous exit rate η, and the elasticity parameter ε. The estimates map to a joint distribution of characteristics in the simulated population, which are shown in table 4.

Across the whole population, the mean and standard deviation of valuations θ_i is equal to 47 and 28, respectively. Workers with higher valuations are more likely to participate in the gig economy, all else equal, so participants exhibit higher valuations equal to 211 on average. This valuation would translate to a variable policy flow utility (*i.e.*, $u(h_i^*(\omega_V), \omega_V; \theta_i)$) of £1,398. I discuss the magnitude of these flows net of outside options in the next section.

The mean outside option for participants equals £674 with a standard deviation and median of £491 and £608, respectively. Since the average participant works approximately 50% FTE in the gig economy, it is useful to compare this with the median earnings of a part-time worker in the UK.[13] The average gig workers' outside option is just one quarter of this amount, which implies these individuals have unattractive alternatives. The mean outside option for the whole population is large—£9,744—because the vast majority of workers will not be drawn into the gig economy given any plausible variation in their economic environment.

The estimation finds a moderate negative correlation between gig work valuations and outside options of -0.62, which reflects the fact that wealthy and high income individuals, who conceivably have high outside options likely have low valuations of gig work since they have low marginal utilities of income. For gig participants, the

[13] The Office for National Statistics classifies this as somebody who works less than 30 hours per week.

Table 3: Parameter Estimates

$\zeta_{1:5}$	$\hat{\zeta}_{1:5}$	$\zeta_{6:10}$	$\hat{\zeta}_{6:10}$
μ_θ	3.70	μ_ν	12.66
	(0.07)		(0.03)
σ^2_θ	0.30	σ^2_ν	4.54
	(0.03)		(0.03)
$\sigma_{\theta,\nu}$	-1.08	σ^2_ϕ	0.14
	(0.05)		(0.01)
λ	1.00	κ	39.41
	(0.13)		(1.13)
σ^2_ρ	0.03	ψ	0.27
	(<0.01)		(<0.01)
μ_P	101.82	σ_P	24.08
p	0.94	β	$0.95^{1/12}$
η	0.07	ε	$\Delta\,\hat{\log}(h) \cdot \log(1+p/\hat{\kappa})$

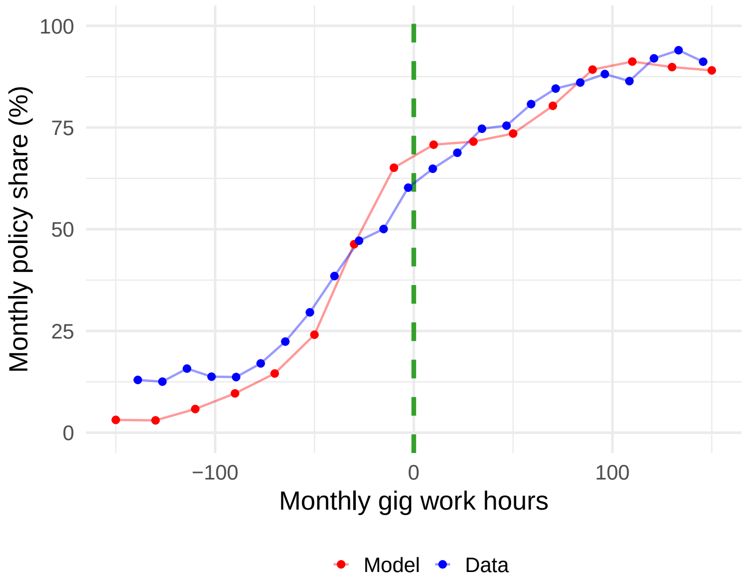
Notes: The top panel of this table presents estimates of the structural parameters from the model. Standard errors are contained in the parentheses, which are estimated as described in subsection 5.1. The second panel shows the variable policy premium and the mean of the quoted fixed premium distribution used in the estimation, which correspond to the empirical averages of these parameters, as well as the set discount factor.

Table 4: Simulated Population Characteristics

Statistic	Population	Participants
Mean valuation θ	47.24	211.17
SD valuation θ	28.07	48.81
Mean misperception ϕ	1.00	1.04
SD misperception ϕ	0.39	0.11
Mean outside option ν	9,744	674
SD outside option ν	1,258	491
Correlation $\rho_{\theta,\nu}$	-0.62	-0.32
Correlation $\rho_{\theta,\phi}$	0.00	-0.27
Correlation $\rho_{\nu,\phi}$	0.00	0.53

Notes: This table presents statistics that describe the simulated population. The first column shows these statistics for the entire population, while the second column conditions on participating in the gig economy.

Figure 6: Model Policy Choice



Notes: This figure compares the model output with the data. The red line reflects the model while the blue line illustrate the data.

negative correlation is attenuated to -0.32 by selection into the gig economy. Namely, workers with high outside options must have high valuations to justify participating.

Misperceptions amongst gig workers are not severe because of learning. Nonetheless, the average gig worker is slightly optimistic because those with high misperceptions are more prone to entering. The average participant overestimates the value of gig work ($\phi_i - 1$) by 4%. Further, gig workers' misperceptions ϕ_i exhibit a significant standard deviation of 11%.

The participation decision drives a negative correlation of -0.27 between misperceptions and valuations for gig workers. Intuitively, this reflects two forces. Firstly, regression to the mean; individuals with a high valuation are likely to have a less extreme misperception given the variables are uncorrelated. Secondly, individuals with low valuations are more likely to have optimistic misperceptions, if they are participating in the gig economy.

Aside from individual specific characteristics, the model implies a reasonable degree of concavity of utility with respect to hours worked in the gig economy (*i.e.*, $1 - 1/\varepsilon$) equal to 0.59. The speed of learning is fast; misperceptions erode by 50% at the end of the first period of work in the gig economy.

Concerning the stochastic element of the model, the standard deviation of valuations shocks is estimated to be 0.18. This implies that constant individual level valuations are responsible for 79% of the estimated variation in valuations (*i.e.* $\sqrt{\mathbb{V}(\theta_i)/\mathbb{V}(\theta^{\rho}_{i,t})}$). These shocks can cause individuals to temporarily exit the gig economy and receive their outside option at a discount ψ estimated to be 27%.

Table 5 compares the empirical moments with those from the estimated model. Overall, the model fits the 23 empirical moments well; the model's predictions are close to the data. Figure 6 provides visual confirmation by contrasting the data with model predictions of policy and hours choices. The quality of the fit supports the view that the model captures structural elements of workers engagement with the gig economy.

6 Welfare and Counterfactuals

This section describes the implications of the estimated model for the gig work surplus, and considers worker welfare in counterfactual scenarios. Specifically, I analyse the impact of mandatory benefits for workers that exceed an hours threshold in the gig economy, which reflects aspects of California's Proposition 22, and the introduction of the variable policy, which serves as a real example of reduced participation costs. Lastly, I examine how misperceptions stymie the gig work surplus.

Broadly, the analysis reveals a large gig work surplus, which is concentrated amongst low-hours workers. The allocation of the gig work surplus across the hours distribution poses policymakers with a trade-off between guaranteeing costly protections for full-time workers and maintaining the appeal of gig work to the majority of participants. The Proposition 22 counterfactual, which leads to an overall decrease in worker welfare if workers bear over 40% of the associated costs, crystallizes this point. Fixed costs to gig work, which make dabbling in the gig economy unattractive, impose significant losses via reduced participation. Eradicating misperceptions increases the gig work surplus by 21%, which stems almost equally from correcting optimistic and pessimistic perceptions.

6.1 The Gig Work Surplus

In this subsection, I measure the gig work surplus as the difference between the participants normative flow utility and their outside option. Figure 7 presents the esti-

Table 5: Model Fit

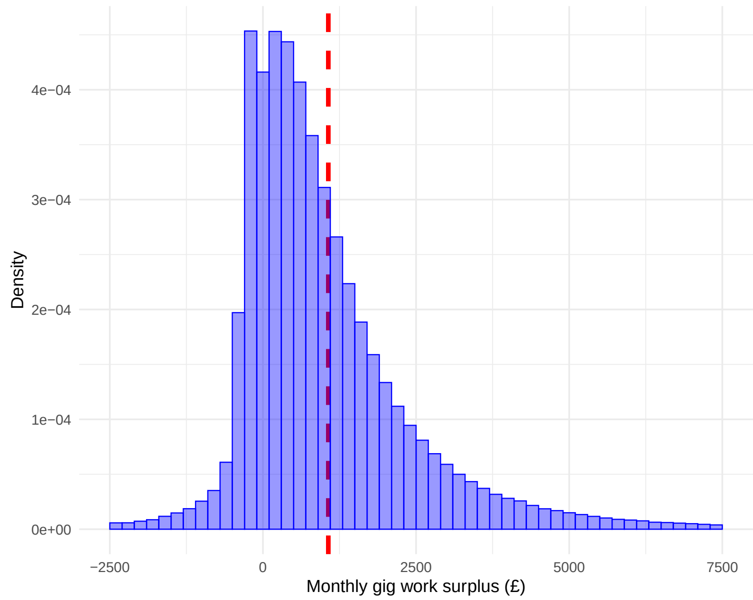
Moment	Data	Model
Labor market share (%)	3.6	3.8
Variable policy share (%)	66.8	68.9
Mean hours per month, variable policy	53.4	58.1
SD hours per month, variable policy	48.4	37.5
Mean hours per month, fixed policy	95.3	104.5
SD hours per month, fixed policy	68.6	74.8
Share non-cost-minimizing (%), variable policy	11.6	9.4
Share non-cost-minimizing (%), fixed policy	60.6	62.3
Mean hours per month from cost-minimizing, variable policy	40.1	40.9
SD hours per month from cost-minimizing, variable policy	36.6	47.3
Mean hours per month from cost-minimizing, fixed policy	55.6	40.8
SD hours per month from cost-minimizing, fixed policy	41.7	31.0
Hazard rate for cost-minimizers (%), variable policy	28.9	23.8
Hazard rate for cost-minimizers (%), fixed policy	20.7	17.6
Hazard rate for non-cost-minimizers (%), fixed policy	29.2	38.3
Decline in hours per month for non-cost-minimizers, variable policy	-10.2	-9.7
Decline in hours per month for non-cost-minimizers, fixed policy	2.6	2.9
Mean quoted fixed premium (£), variable policy	97.0	95.6
Mean quoted fixed premium (£), fixed policy	106.5	104.4
SD quoted fixed premium (£), variable policy	25.1	19.9
SD quoted fixed premium (£), fixed policy	24.3	26.5
Share of zero hours months (%)	5.5	5.9
Mean within worker SD hours per month	31.0	37.7

Notes: This table presents the targeted empirical moments alongside their model implied counterparts. The first column contains the empirical moments and the second column contains the model analogue.

mated distribution of the monthly gig work surplus. The mean monthly surplus for a gig worker equals £1,066, which is approximately one-third of the average employee's monthly income in the UK. This aggregate number masks significant heterogeneity with a standard deviation of £1,775. Moreover, the ratio of the 30^{th} to 70^{th} percentile is equal to 6.5.

A minority of workers suffer a negative surplus because of their misperceptions

Figure 7: The Gig Work Surplus Distribution



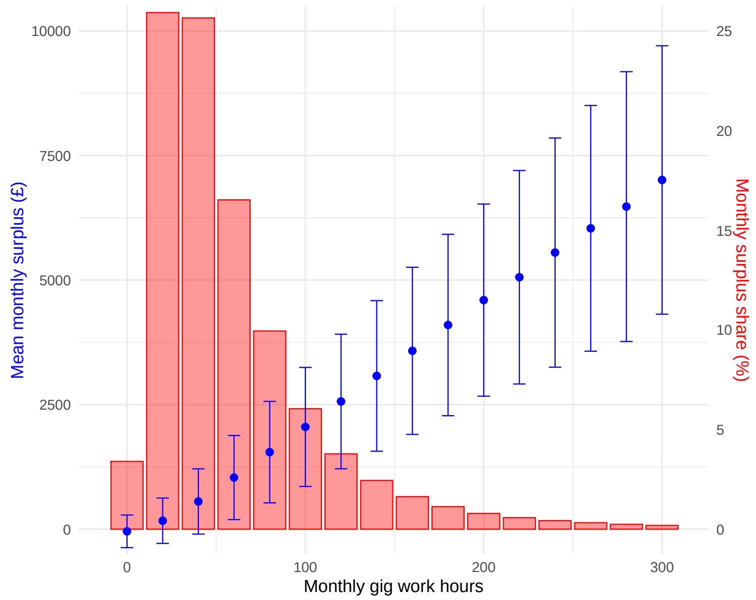
Notes: This figure shows the histogram of the monthly gig work surplus from the estimated model. The red dashed line shows the mean of this distribution.

and temporary exit. In an average month, 16% of participants receive a negative surplus due to misperceptions.[14] However, 45% of each new entering cohort would be better off with their outside option and they lose £1,183 on average. Further, in a typical month, a worker who temporarily exits loses £291 relative to the full value of their outside option. These results reconcile the tension between the fast take up of gig work and the prevalence of negative experiences, as well as significant churn in participation.

It is also informative to consider where the gig work surplus falls along the hours distribution. Figure 8 presents the average monthly gig work surplus by hours bin in blue and the share of the total gig surplus falls in each bin in red. Two clear patterns emerge. Firstly, the surplus increases roughly linearly with hours, which implies the hourly surplus is roughly linear on average. Secondly, the total worker surplus generated by the gig economy is concentrated amongst workers who work less the 50% full-time. This makes it difficult for regulators to ensure protections for full-time gig workers without damaging the surplus of low hours workers, who comprise the ma-

[14] Jäger et al. (2022) offers a useful comparison to this result. This paper finds that "if workers had correct beliefs, at least 10% of jobs... would not be viable", which is close to the 16% number found here.

Figure 8: The Gig Work Surplus by Hours Worked



Notes: This figure plots the mean monthly gig work surplus for participants by different hours bins. The error bars show a one standard deviation in the monthly gig work surplus. The red bars show the share of the total gig work surplus accounted for by each hours bin.

jority of the gig work surplus.

I provide three benchmarks to compare these results against. Firstly, the mean hourly surplus is £12.04, which represents between 70 to 80% of the likely wage in the market after accounting for idle time. Secondly, I asked survey respondents "How much would your earnings have to drop per month for you to stop doing this type of work?". With significant caveats, the response to this question should reflect the difference between an individual's value of gig work and their outside option. Comfortingly, the median response is £462, which is roughly in line with the estimates presented here.[15] Thirdly, Chen et al. (2019) estimate a median "base" surplus of £571 using an exchange rate of dollars to pounds of 0.8. Thus, the results presented here are consistent with the scant evidence on the gig work surplus.

Discussion. The gig work surplus is unambiguously large, both in terms of its level (*i.e.*, the monthly surplus) and the rate at which it accrues (*i.e.*, the average hourly surplus). Taking the numbers above seriously, at an aggregate level, this part of the

[15] Survey responses were censored from above at £1,000 so it is not possible to compare means.

gig economy alone generates £15bn (= 32.8 million × 3.59% × £1,066 × 12) in worker surplus annually.

Broadly, workers can derive a large surplus through either a high valuation of gig work or a low outside option, or both. In terms of valuations, workers can derive value from the gig economy through many channels. Income earned from gig work provides utility via consumption. These additional earnings may be particularly valuable if workers have a high marginal utility of income. There are reasons to believe this is the case. Most of these individuals are in the bottom half of the income distribution and are likely to receive negative income shocks prior to entry into the gig economy (Cornick et al., 2018; Koustas, 2019).

Gig work also entails a unique combination of amenities. Workers can pick their hours, do not have a boss, are paid weekly, and receive some income insurance because they can earn more or less depending on their circumstances. Individuals who especially value these amenities are more likely to select into gig work and, in turn, increase the gig work surplus.

A large gig work surplus could also come from low outside options. This could be leisure, which may deliver little utility due to underemployment, complementarity with income, or other poor employment opportunities. Gig work may facilitate other high value activities when workers are not engaging with the gig economy that are not feasible otherwise, which would also manifest as a low outside option. Further, many gig workers are foreign-born with English as a second language, which could make traditional employment difficult to find. At an extreme, although food delivery platforms implement right to work checks, there are anecdotal stories that these checks are possible to circumvent (*e.g.*, by working under a different identity) such that gig participants may not have the opportunity to work elsewhere.

6.2 California's Proposition 22

In 2020, California passed a ballot initiative—Proposition 22—that provided gig workers with a range of new protections, while denying these workers the broader benefits received by employees.[16] One of the benefits is a health insurance stipend for workers who meet an hours threshold. Precisely, workers who average more than 25 hours per week over a quarter are entitled to 100% of the average premium for a specified health insurance policy. Workers who average between 15 and 25 hours per week over the

[16] Proposition 22 exempted digital rideshare and delivery platforms from Assembly Bill 5.

corresponding period are entitled to half that amount.[17]

While the setting for this paper is the UK, the Proposition provides a useful benchmark to think about the scale and structure of protections that may become available to gig workers in the UK and elsewhere. Therefore, I consider a counterfactual where workers who exceed 100 hours per month receive a fixed pecuniary benefit of £400, and that workers who work between 60 and 100 hours per month receive £200.

The legislation places the statutory incidence on platforms to pay workers who qualify for benefits but the economic incidence will fall on a combination of the platforms, customers, and workers themselves. Importantly, it is the economic incidence that will determine the welfare effects of this policy (Gruber, 1994). To this end, I assume that the incidence on workers will manifest as a reduction in all their hourly earnings. An hourly earnings penalty is the most transparent way to model how platforms may pass on any costs. The important aspect of this assumption is that it imposes a variable cost on workers. This is a reasonable benchmark because *a priori* platforms cannot determine which workers will qualify for benefits, and multi-homing across platforms will undermine targeted incidence.

Since estimating the likely degree of incidence is outside the scope of this paper, I consider a range of incidence s from zero to full in order to study the welfare impacts of the counterfactual policy. The penalty on hourly earnings $c(\bullet)$ associated with incidence s is found by numerically solving

$$c(s) \cdot H\big(c(s)\big) = s \cdot \Bigg(200 \cdot N_{200}\big(c(s)\big) + 400 \cdot N_{400}\big(c(s)\big)\Bigg),$$

where $H(\bullet)$ is the aggregate number of hours worked, and $N_{200}(\bullet)$ and $N_{400}(\bullet)$ denote the number of workers who qualify for the respective benefits.

This policy is non-marginal; it introduces sizeable non-convexities into workers' economic environment and, thus, lends itself to evaluation in a structural model. Workers can exhibit four potential labor supply responses: (i) non-participants may join the gig economy as they are encouraged by the benefits, (ii) some gig workers may exit as the wage penalty reduces their surplus below zero, (iii) individuals close enough to the hour thresholds may discretely increase their hours to qualify for the benefits, and (iv) the remainder of participants will reduce their hours as their hourly earnings fall to cover some proportion of the cost of the benefits. Specifically, work-

[17] The text of the law can be found here at the bottom of page 32.

ers' labor supply in the gig economy will follow

$$h^*_{i,t}(\omega) = \begin{cases} \left(\frac{\hat{\theta}^{\rho}_{i,t}}{p(\omega)+\kappa+c}\right)^{\varepsilon} & \text{if } \rho_{i,t} > \rho_{25}(\nu_i, \hat{\theta}_{i,t}), \\ 25 \times 4 & \text{if } \bar{\bar{\rho}}(\nu_i, \hat{\theta}_{i,t}) < \rho_{i,t} < \rho_{25}(\nu_i, \hat{\theta}_{i,t}), \\ \left(\frac{\hat{\theta}^{\rho}_{i,t}}{p(\omega)+\kappa+c}\right)^{\varepsilon} & \text{if } \rho_{15}(\nu_i, \hat{\theta}_{i,t}) < \rho_{i,t} < \bar{\bar{\rho}}(\nu_i, \hat{\theta}_{i,t}), \\ 15 \times 4 & \text{if } \bar{\rho}(\nu_i, \hat{\theta}_{i,t}) < \rho_{i,t} < \rho_{15}(\nu_i, \hat{\theta}_{i,t}), \\ \left(\frac{\hat{\theta}^{\rho}_{i,t}}{p(\omega)+\kappa+c}\right)^{\varepsilon} & \text{if } \underline{\rho}(\nu_i, \hat{\theta}_{i,t}) < \rho_{i,t} < \bar{\rho}(\nu_i, \hat{\theta}_{i,t}), \\ 0 & \text{if } \rho < \underline{\rho}(\nu_i, \hat{\theta}_{i,t}), \end{cases} \tag{18}$$

where $\underline{\rho}(\bullet), \bar{\rho}(\bullet), \rho_{15}(\bullet), \bar{\bar{\rho}}(\bullet)$, and $\rho_{25}(\bullet)$ are defined in appendix E. Workers' policy choices and participation from the gig economy follow as before via backward induction. The behavioral responses will exacerbate the cost of these benefits to platforms and, consequently, the burden placed upon workers.

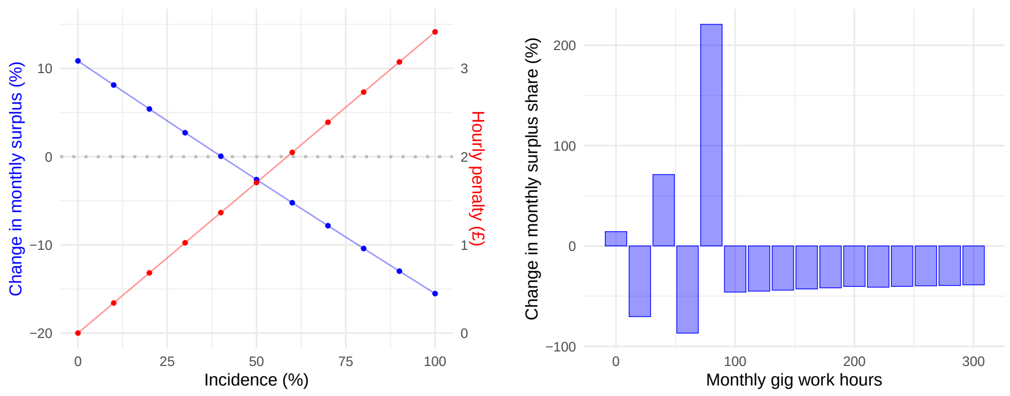
The welfare impacts of this policy are illustrated in figure 9. Panel 9a shows the gig work surplus under a range of different incidence levels. The analysis suggests that even a low degree of incidence on workers—anything greater than 40%—would cause this hypothetical policy to decrease worker welfare. This level of incidence leads to a £2.01 drop in hourly earnings. As a comparison, Kolstad and Kowalski (2016) find that mandated employer-sponsored health insurance in Massachusetts was passed onto employees at a rate of 70 cents on the dollar. That said, if there is minimal pass-through to workers, the policy could increase worker welfare by as much as 11%.

Panel 9b shows how the distribution of the gig work surplus changes across hours worked when incidence is evaluated at 40% (*i.e.*, keeping the total surplus constant). The share of the surplus that falls into the bins (40,60] and (80,100] grows substantially because workers bunch at 60 and 100 hours in order to received the mandated benefits. Everywhere else the share of the surplus falls since other hours bins see a decrease in the number of workers and the remaining workers face an hourly wage penalty.

6.3 The Introduction of the Variable Policy

The introduction of the variable H&R policy constitutes a real example of a reduction in the fixed costs associated with gig work. Therefore, in this counterfactual experiment I compare the gig work surplus in the *status quo* with a world without the

Figure 9: Proposition 22 Counterfactual



(a) The Gig Work Surplus by Incidence

(b) %Δ Gig Work Surplus Share by Hours

Notes: This figure plots outcomes under the Proposition 22 counterfactual policy. Panel 9a plots the percentage change in the total gig work surplus as a function of incidence in blue. The red line plots the hourly wage penalty associated with the different degrees of incidence. The dotted grey line shows the total surplus in the *status quo*. Panel 9b plots the percentage change in the share of the gig work surplus associated with each hours bin at an incidence level of 40%.

variable policy.

Without the variable policy it is possible that fixed policy premiums may adjust. Although there is little evidence of this in the market, I consider welfare with and without adjustment in fixed premiums.I make two assumptions to do this. First, insurers' costs are linear in hours worked; discussions with the firm indicate that exposure to risk (*i.e.*, time on the road) is the greatest single driver of claims and that the relationship is linear up to a reasonable approximation. Second, the fixed policy market is competitive such that profits are zero (Einav and Finkelstein, 2011).

Under these assumptions I can back out the expected claims from an hour of driving as observed total fixed policy premiums collected divided by the sum of hours worked under the fixed policy. This implies an hourly expected claims cost C of £0.95 per hour, which is very close to the variable policy premium. I assume that the firm will adjust all fixed policy premiums by a proportional amount α, so that a given monthly premium P_i will become $\alpha \cdot P_i$. I solve for α by requiring zero profits

$$H(\alpha) \cdot C = Q(\alpha),$$

where $H(\bullet)$ is aggregate hours worked and $Q(\bullet)$ denotes total premiums.

Again, this is a non-marginal counterfactual experiment that is well suited to a

Table 6: % Change in the Gig Work Surplus under Different Scenarios

Scenario	Agg. Surplus	Employment Share	Mean Surplus
Status quo	£40	3.8%	£1,066
No variable policy (NVP)	-4.7	-4.8	0.1
NVP with endogenous P_i	0.8	-2.4	3.2
No fixed policy	0.6	0.3	0.4
No misperceptions	20.6	23.0	-2.0
Half SD of misperceptions	15.2	9.3	5.4
No optimists	8.7	-8.3	18.6
No pessimists	11.7	31.5	-15.0

Notes: This table shows the welfare affects of removing the variable policy. Column 1 shows the scenario considered and columns 2, 3, and 4 show the *per capita* surplus, the employment share of the gig economy, and the gig work surplus conditional on working, respectively. The top panel shows the base levels of these variables, and the bottom panel shows the percentage changes under the different scenarios.

structural model. The introduction of the variable policy causes some workers to switch policy in steady state and, in turn, to reduce their hours. Further, new workers will enter some of whom may be worse off with hindsight because of misperceptions.

Table 6 compares outcomes under the *status quo* and the counterfactuals. The first row shows that without the variable policy and no adjustment in fixed policy premiums the gig work surplus is reduced by 4.7%, which stems mainly from a reduction in gig work participation. This means that, in aggregate, the introduction of the variable policy constituted a £709mn boon for workers. In contrast, the third row reveals that welfare would be marginally higher without the fixed policy because overly optimistic individuals select into the fixed policy but would be better off on the variable policy.

Interestingly in row 2, if fixed policy premiums adjust to the removal of the variable policy, then worker welfare is slightly higher in a world without the variable policy. Participants in the gig economy exhibit a negative correlation between valuations and misperceptions, so that many low hours workers who select the variable policy are overly optimistic. Consequently, a small amount of fixed costs can prevent these individuals from making the mistake of entering. However, this scenario entails that fixed premiums should have risen by 30% since 2017—something that has not been observed. This highlights that competition amongst firms that serve gig workers is crucial to the gig work surplus.

6.4 Reducing Misperceptions

Misperceptions cause an allocative inefficiency in the gig economy: some optimistic workers participate in the gig economy when, with hindsight, they should not, meanwhile some pessimistic individuals would be better off inside the gig economy but are not. This inefficiency is material. Row 4 in table 6 reveals that the gig work surplus would be 20.6% higher absent misperceptions.

Interestingly, both sides of this allocative inefficiency are roughly equally responsible for the welfare loss albeit in very different ways. Correcting all optimists' misperceptions causes a 8.3% reduction in participation but a 18.6% increase in the mean surplus. In contrast, if all pessimists are disabused of their misperceptions, there is a 31.5% increase in the employment share and a 15% fall in the typical surplus.

The model suggests that policies aimed at reducing misperceptions could be a fruitful pursuit. Halving the standard deviation of misperceptions obtains three quarters of the welfare gains from eradicating misperceptions. Think-tanks have touted policies that require platforms to increase transparency by, for example, providing predictions of hourly earnings to workers. It remains to be seen how these information treatments would translate to a reduction in misperceptions.

7 Conclusion

This paper evinces new empirical patterns about gig work including the fact that non-cost-minimizing behavior is correlated with workers' subsequent hours dynamics and survival in the gig economy. These findings motivate a model where individuals have heterogeneous valuations of gig work and outside options, and workers suffer from misperceptions about the value of gig work which they learn about through participation. Survey evidence suggests that misperceptions could stem from unanticipated earnings, costs, and other difficulties associated with gig work.

The estimated model implies a large gig work surplus of around £1,000 for the average participant although there is subsequent heterogeneity. One in six gig workers are left worse off relative to their outside option because they enter the gig economy due to an overly optimistic valuation. The majority of the gig work surplus is located at the lower end of the hours distribution causing a trade-off for policymakers between providing full-time workers with protections and maintaining the appeal of gig work to most participants who only work part-time. Fixed costs to participation and misperceptions are also found to substantially reduce the gig work surplus.

To finish, I note that, although this study suggests a large gain for workers from the emergence of the gig economy, the gig work surplus could be higher yet. Future research should evaluate ways to achieve this goal. Fruitful avenues may include decentralizing prices to drivers, encouraging and facilitating multi-homing across platforms, more information provision to drivers, and commission caps (Fisher, 2024).

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Appendices

A Policy Choice

In this appendix, I present evidence from switchers that workers are trying to minimize costs with their insurance policy choice, and I discuss other potential influences on this decision.

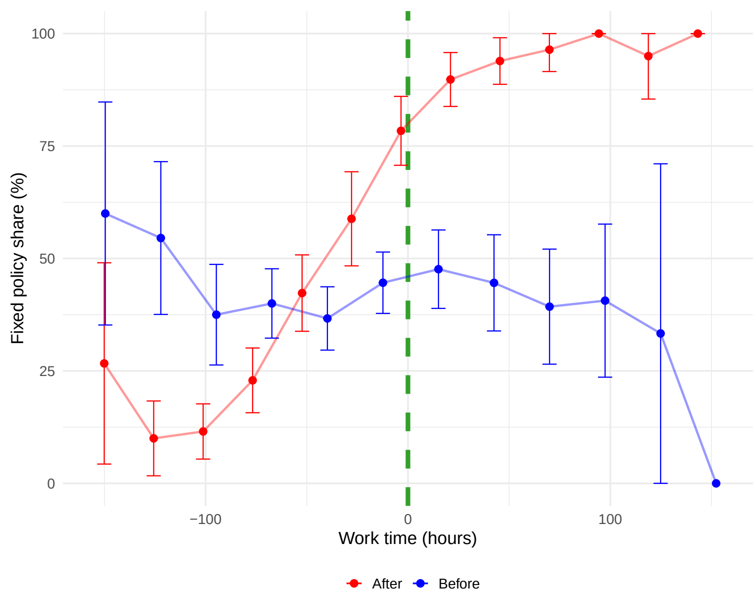
A.1 Cost-Minimization Motive

The primary difference between the fixed and variable policy is the tariff structure. The variable policy is paid for by the hour while the fixed policy comes with a fixed monthly cost. Therefore, gig workers will select the policy that minimizes their costs *ceteris paribus*. In practice, this means that workers who work less than 100 hours or so will generally be better off on the variable policy.

This logic is supported by figure 2, which shows the share of workers on the fixed policy across different hours bins. The diagram reveals that workers are increasingly likely to take the fixed policy as they work more hours. This pattern is consistent with a rational cost-minimizer who suffers from imperfect foresight. As described in the main text, a cost-minimizer with perfect foresight would behave in accordance with the dashed green line. Introducing noise into this individual's problem would distort the step function into an upward sloping line that crosses the break-even point at 50%. The exact shape of the line would depend on the distribution of the noise. Thus, the data is consistent with workers that try to cost minimize but who are subject to *ex ante* misperceptions and/or *ex post* shocks.

The few workers who switch, and who are excluded from the main analysis, can offer further support to the cost minimization hypothesis. Figure A1 shows that workers who switch policy initially make very poor decisions from a cost-minimization perspective. The blue line describes choices before switching; there is no discernible increase in the probability of opting for the fixed policy as hours worked increase. However, after switching, policy choices reflect a strong cost-minimizing tendency. The increasing red line indicates that the fixed policy share increases with hours. This evidence supports the view that switchers seek to correct non-cost-minimizing choices, which in turn supports the hypothesis that individuals want to minimize costs in their policy choice when they first enter the gig economy.

Figure A1: Fixed Policy Share by Hours Worked, Before and After Switching



Notes: This figure plots the share of workers who are on the fixed policy by hours bins for switchers before and after they switch. Each observation in a bin is a worker, so the hourly bin than an individual falls into is determined by their average monthly hours. The green dashed line indicates the perfect cost-minimizer's policy choice, which is vertical at the break-even point. Standard errors are constructed by applying the law of large numbers to a Bernoulli random variable (*i.e.*, $\sqrt{p \cdot (1-p)/N}$ where p is the share of policies on the fixed policy in a bin and N is the number of observations in that bin). In total, this figure contains 588 workers.

A.2 Alternative Motives

Other factors besides cost minimization could influence the choice between the fixed and variable policies. In this subsection, I provide a taxonomy of these factors.

Coverage. The hourly policy only offers third party coverage, therefore, drivers who desire more comprehensive coverage may select a fixed policy despite higher costs. I deal with this by adjusting premiums for reported WTP for additional coverage from the survey, when individuals opt for greater coverage. Further, I check the robustness of reduced form results to restricting attention to third party only policies in appendix C.

Insurance value. The different policy choices imply different variances in costs and overall income. In this case, the policy that minimizes variance in income would have some value aside from its implications for the expected level of costs. Although the fixed policy minimizes variance in costs, the variable policy minimizes variance in overall incomes since increases in costs from more hours worked are offset with higher earnings. The overall result is that income is more steady. As such, any insurance value would push in the direction of selecting the variable policy.

Quantitatively, reasonable degrees of risk aversion and the likely magnitude of fluctuations in income imply this story is not a significant driver of any patterns in the data. Consider an individual with CARA preferences and a degree of risk aversion equal to 0.0016 (Handel and Kolstad, 2015). In this case, reducing the standard deviation of monthly income by £35 would increase money-metric utility by less than £1. Moreover, workers exhibit a slightly excessive tendency to opt for the fixed policy, which goes against this mechanism.

Engine size. Only scooters with an engine size of up to 125cc can opt for the variable policy. Fortunately, I can observe engine size with the quote data and exclude them from the analysis. Less than 1% of engine sizes exceed the threshold.

Liquidity. If agents are illiquid, then they may not be able to afford the up-front cost of the fixed insurance policy. This would push such individuals towards the variable policy regardless of their expected hours. Therefore, some of these individuals may find it more economical to select the fixed policy but are not able to do so. Given that few variable policyholders would reduce costs by being on the fixed policy, this does not seem to be a significant friction. Moreover, if illiquid workers are able to access credit, then liquidity issues should not affect their policy choice. And, again, if anything, there is an over enthusiasm for selecting the fixed policy as shown in figure 2 by the fact that the blue line crosses zero on the x-axis above the 50% level.

Taxi meter effect. The taxi meter effect would occur in this context if workers receive higher utility gross of insurance costs from the same number of hours on the fixed policy than on the variable policy (Lambrecht and Skiera, 2006). The motivating example, and origin for the name of the effect, is that taxi rides are less enjoyable simply because the customer can see the fare tick up on the taxi meter. Such an effect would push workers to choose the fixed policy over the variable policy *ceteris paribus.*

Present bias. Sophisticated present bias pushes workers towards selecting the fixed policy, while the effect of naïve present bias is ambiguous. An agent who is aware of their present bias (*i.e.*, sophisticated) may prefer to opt for the fixed policy to correct their inefficiently low level of labor supply (Lockwood, 2020). In the same vein, naïve present bias may push workers to choose the fixed policy since they overestimate how much they will work in the future (Augenblick and Rabin, 2019). On the other hand, naïve present bias may cause workers to favour the variable policy to avoid the upfront cost of the fixed policy, if workers suffer from present-bias over money or the timely consumption opportunities that it brings.

B Data Cleaning and Filters

In this appendix, I describe the data cleaning procedures and the subsequent filters I apply to the data in order to arrive at my analysis sample. I also discuss the survey and quotes data in more detail.

B.1 Data Cleaning and Filters

The raw data is in calendar month tranches, which were received from the firm, with observations at the job level (*i.e.*, each observation is a food delivery). I collapse each tranche down to the user-policy level, or just to the user level in the case of variable policy holders. Then, a variable policy holder's monthly observation is associated with a calendar month, while I merge fixed policy holders' policies that were divided over two calendar months such that their month corresponds to a 30 day policy duration. I then drop any user-policy-month-year duplicates, and removed any fixed policies that exceed 30 days. Some fixed policy holders' policies are further fragmented because of changes to their policy over the course of its duration (*e.g.*, a customer might have switched their coverage). I combine these policies by checking start and finish dates of the fragmented policies to see combinations of policies that consist of precisely 30 days. After this step, I drop any policies that are shorter than 14 days. Lastly, I trim observations according to monthly work time and premiums at the 0.1% percentile in order to remove outliers.

Hours of work may be understated for variable policy holders in the their first month because an observation is associated with a calendar month such that they may begin work halfway through a month. To deal with this, I *pro rata* work hours of these individuals according to what they did work while they were active in that month and, if there is less than two weeks left in the month, then I drop these partial observations. I have tested robustness to the two week threshold (*e.g.* using less than one week or less than three weeks) and the effect on the data is minimal. A similar problem arises for both fixed and variable policyholders in their final month before exiting; if workers leave after one week into their final month then their hours are not reflective of their engagement in the gig economy. I resolve this issue analogously.

I apply four filters after data cleaning. Firstly, I remove annual policy holders who make up a small fraction of customers, hence, their omission from the data cleaning discussion. Secondly, I keep only individuals who start after January 1 2019 since before this point the firm did not offer a consistent menu of policies. Thirdly, I identify workers who have more than one stint in the gig economy by flagging breaks of four months or longer. For these workers, I keep only their first stint in the gig economy. Finally, I remove individuals from the main analysis who switch policy during their initial spell.

B.2 Survey Data

I complement the administrative data with survey data. The survey was conducted through the firm by emailing customers, if they had subscribed to receive promotional material. Fixed policyholders were over-sampled because they have a greater tendency to subscribe affirmatively. 500 workers started the survey, of which 336 completed it. Of these, 251 are on the fixed policy.

The survey was sent out twice (the second time as a reminder) in June 2022. Therefore, the workers surveyed are not necessarily in my administrative data and, despite efforts, they cannot be merged. Therefore, to construct categories (*e.g.*, minimizers) I rely on self-reports of hours and the premiums that they face.

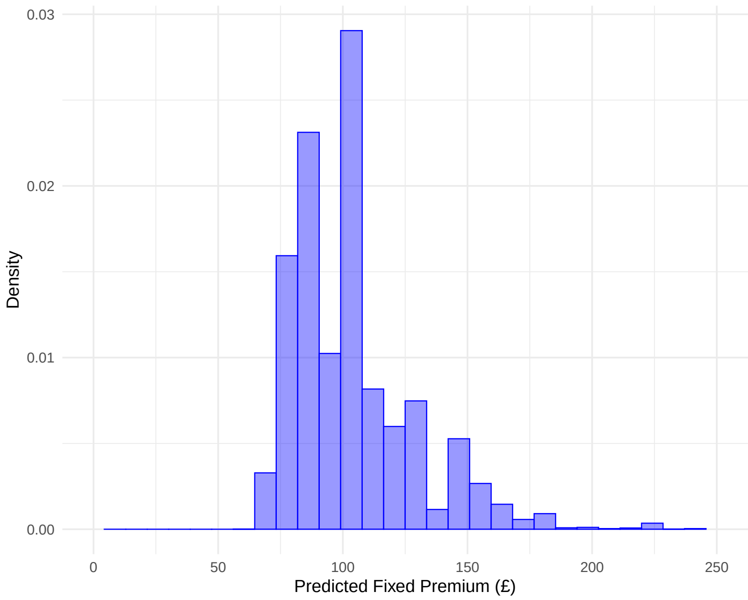
B.3 Premiums and Quotes Data

The firm sent data on the quotes that they have offered to all enquirers over the analysis period. This allows for the observation of an unselected distribution of quotes and, in particular, I can view the fixed premiums offered to variable policyholders.

From the fixed policyholders, it is clear that quoted premiums typically fall shy of realized premiums. To resolve this issues, I non-parametrically predict realized premiums with quoted premiums for fixed policy holders by calculating the average realized premium within £5 quoted premium bins. Then, I use this model to construct counterfactual realized premiums for all other customers. Figure B2 shows the resulting distribution of premiums.

As mentioned in the text, I adjust fixed policy premiums for customers whose policies entail coverage beyond third-party damage. To do this, I use information on willingness to pay for additional coverage, which is reported in the survey. This adjustment constitutes a reduction in the fixed premium paid by fixed policyholders who opt for extra coverage. To calculate the reduction, I take the average WTP for additional coverage conditional on that amount being higher than the additional premium charged for the higher level of coverage. That is, I calculate the average WTP for extra coverage for those who find it worthwhile to opt for that coverage.

Figure B2: Empirical Distribution of Fixed Premiums



Notes: This figure plots the empirical distribution of offered fixed policy premiums from the firms quote data.

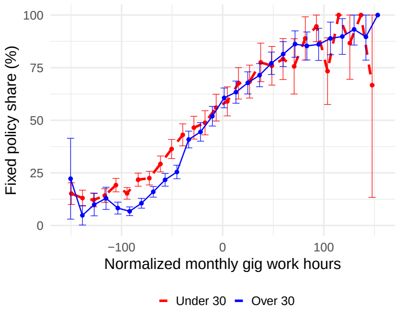
C Robustness Checks: Reduced Form Evidence

In the main body of the paper, I present a number of reduced form facts. In this appendix, I present robustness checks which show that the patterns in the data persist across different subgroups of the population, with different definitions of categories, and over different time periods in the data. I also present additional empirical evidence.

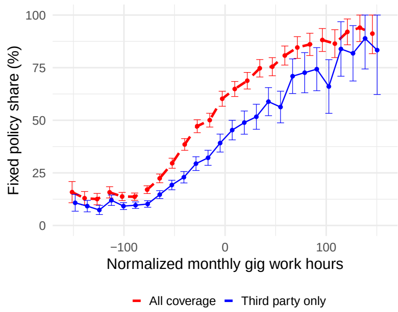
Figure C3 shows the analogue of figure 2 for various cuts of the data. Panel C3a shows the share of individuals on the fixed policy for those under and over 30, separately. Broadly, the two age groups show the same pattern, although over 30s are slightly more effective at minimizing costs by selecting the variable policy more frequently, when hours are below the break-even point. Panel C3b shows the equivalent data when including all types of coverage and when keeping soley third party only policies. Since only fixed policies can include levels of coverage other than third party only, the blue line is mechanically lower than the red line, where the latter reflects the fixed policy share for all types of coverage. Panel C3c shows the share of individuals on the fixed policy for the main analysis sample and for the sample where individuals whose predicted premiums exceed £175 are excluded. Panel C3d shows the fixed policy share for the period of time before the Covid pandemic, and for the course of the Covid pandemic during which there were several lock-downs in UK, where food delivery riders could still work. For transparency, figure C4 shows the fixed policy share by non-normalized hours where the dashed green line represents a perfect cost minimizer who faces the average fixed premium and the variable premium.

Figure C6 shows that the patterns of survival persist for the categories across various robustness checks. Panels C5a and C5b use alternative definitions to construct categories. The former categorizes workers based on whether they minimize their bill of the course of their tenure in the gig economy; and the latter compares average hours with break-even points to categorize workers. Panels C5c and C5d show the patterns of survival for different categories, using the baseline definition, for under and over 30s, respectively. Panels C5e and C5f illustrate the same data for the period before the Covid pandemic and for the course of the Covid pandemic, respectively. Panel C5g exhibits the pattern of survival for different categories, restricting to those on third party only policies. Panel C5h shows the survival trajectories for non-third party only policies by categories. These are necessarily fixed policies, so the diagram excludes pessimistic workers. Panel C5i shows the survival curves of minimizers bro-

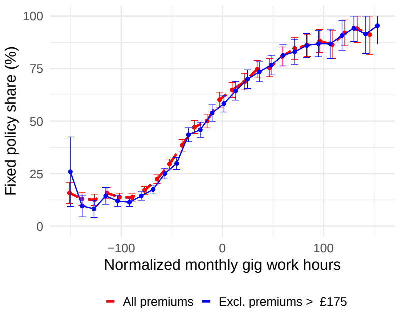
Figure C3: Fixed Policy Share by Normalized Hours for Different Samples



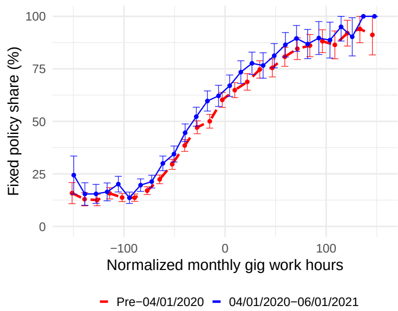
(a) By age



(b) By cover



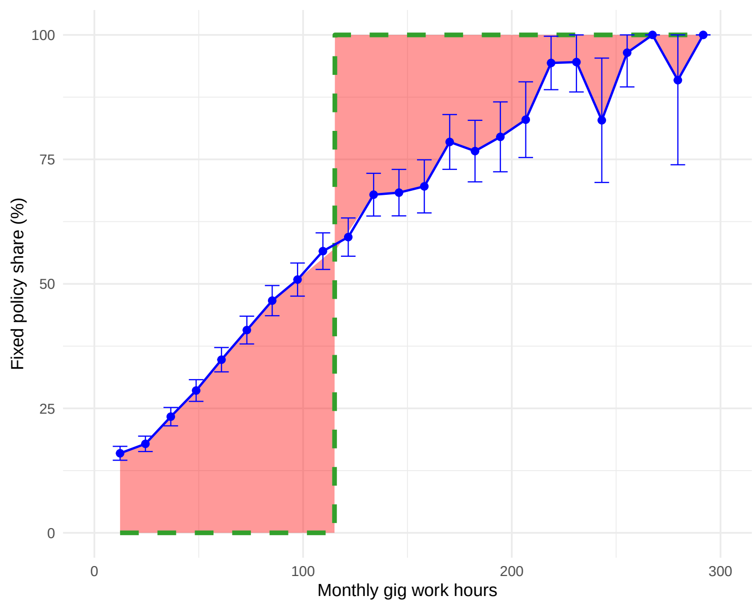
(c) By premiums



(d) By time

Notes: These figures plot the share of individuals on the fixed policy by different groups. Standard errors are calculated by applying the law of large numbers to the average of a random variable that follows the binomial distribution with one trial (*i.e.*, $\sqrt{p_j \cdot (1 - p_j)/N}$ where p_j is the share of responses for a given category j and N is the number of observations).

Figure C4: Raw Fixed Policy Share



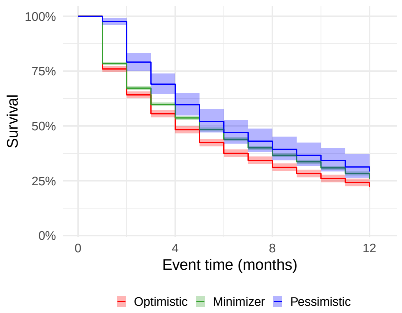
Notes: This figure plots the share of workers who are on the fixed policy by monthly hours bins. Each observation in a bin is a worker, so the hourly bin that an individual falls into is determined by their average monthly hours. The green dashed line indicates the perfect cost-minimizer's policy choice, which is vertical at the break-even point. Standard errors are constructed by applying the law of large numbers to the average of Bernoulli random variables (*i.e.*, $\sqrt{p \cdot (1-p)/N}$ where p is the share of policies on the fixed policy in a bin and N is the number of observations in that bin).

ken down by fixed and variable policy holders. Panel C5j shows the survival patterns of workers who select different types of coverage. Panel C5k shows that survival function for workers preceding and during the Covid pandemic.

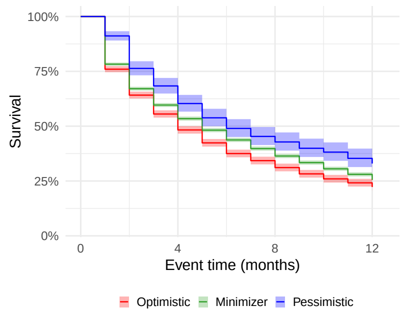
Table C2 reproduces table C1 with alternative controls. Columns (1) to (4) vary the controls included in the Cox proportional hazards model. In order, the columns exclude cover, gender, age, and low hours controls. Table C3 and C4 show the results from linear probability models, which show the same patterns as table C1 using the same controls. Table C3 shows an OLS regression where the outcome variable is the exiting the gig economy within the specified periods of time, while C4 shows the analogue conditional on reaching that tenure.

Figure C6 shows the trajectory of hours, like figure 4, for subgroups of the data. Panels C6a and C6b shows the trajectory of hours for categories using alternative definitions, which are analogous to those in figure C6. Panels C6c and C6d show the trajectory of hours over time for under and over 30s respectively. Panels C6e and C6f

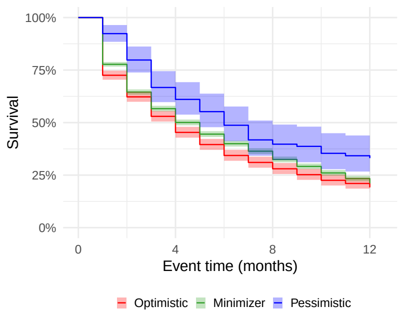
Figure C5: Survival by Categories for Different Definitions & Samples



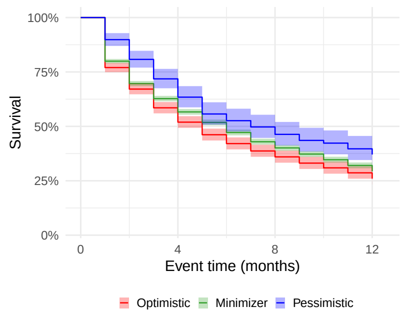
(a) Alternative categories: bill minimization



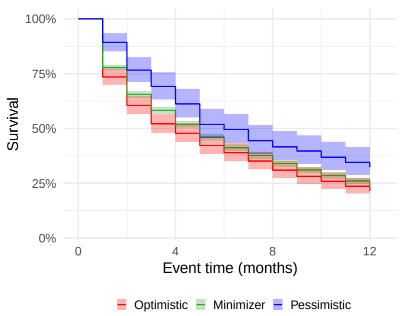
(b) Alternative categories: average hours



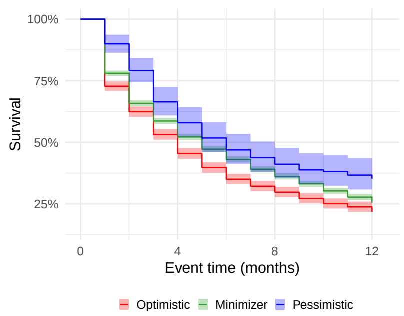
(c) Under 30s



(d) Over 30s



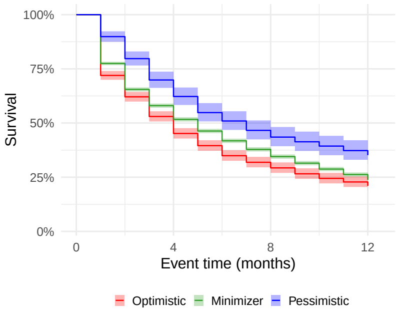
(e) Pre-04/01/202



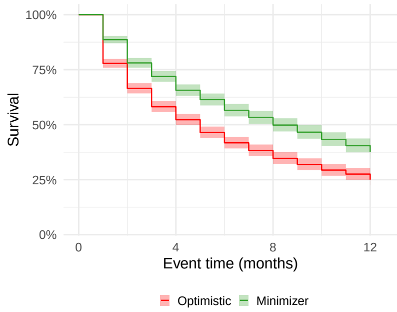
(f) 04/01/2020-06/01/2021

Notes: This figure plots Kaplan-Meier survival curves for different groups in the gig economy. The green, red, and blue lines denote the minimizers, optimistic, and pessimistic categories, respectively. Event time is tenure month in the gig economy (*i.e.*, $t = 1$ is workers' first month in the gig economy so if an individual does not have a second month in the gig economy, then they exit in the first period).

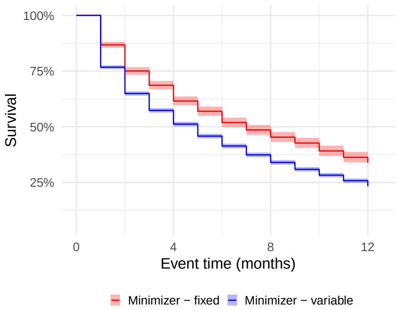
Figure C5: Survival by Categories for Different Definitions & Samples



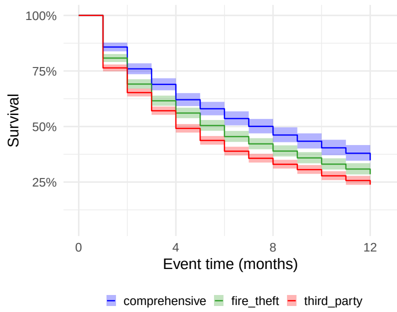
(g) Third party only



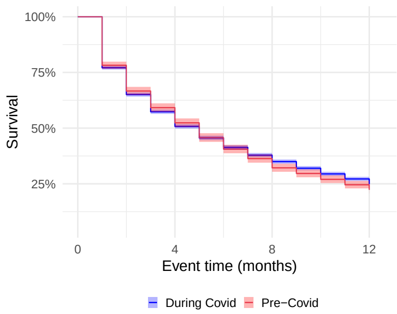
(h) Non-third party only



(i) By type of minimizer



(j) By cover



(k) By time

Notes: This figure plots Kaplan-Meier survival curves for different groups in the gig economy. The green, red, and blue lines denote the minimizers, optimistic, and pessimistic categories, respectively. Event time is tenure month in the gig economy (*i.e.*, $t = 1$ is workers' first month in the gig economy so if an individual does not have a second month in the gig economy, then they exit in the first period).

Table C1: Cox Proportional Hazards Model with Time-Varying Coefficients

	Dependent variable:		
	Tenure in the gig economy (months)		
	All controls	Time controls	No controls
	(1)	(2)	(3)
Mean hours	-0.001^{**}	-0.001^{***}	-0.001^{***}
	(0.0003)	(0.0003)	(0.0003)
Minimizer ($<=$ 2 months)	0.221^{**}	0.181^{*}	0.179^{*}
	(0.100)	(0.095)	(0.095)
Optimistic ($<=$ 2 months)	0.481^{***}	0.378^{***}	0.353^{***}
	(0.104)	(0.098)	(0.098)
Minimizer ($>$ 2 months)	-0.053	-0.067	-0.072
	(0.070)	(0.068)	(0.068)
Optimistic ($>$ 2 months)	0.173^{**}	0.083	0.074
	(0.078)	(0.073)	(0.073)
Low hours	Yes	Yes	Yes
Time controls	Yes	Yes	No
Age	Yes	No	No
Gender	Yes	No	No
Cover	Yes	No	No
Observations	23,969	25,729	25,729
R^2	0.076	0.071	0.066

Notes: *p<0.1; **p<0.05; ***p<0.01. This table shows estimates from a Cox proportional hazards model with time varying coefficients on the categories variable; the effect of this factor variable is allowed to differ between the first two months of a worker's spell and any remaining months. Coefficients reflect percentage changes in the base hazard rate associated with the corresponding variable. The main panel of the table shows estimates for these coefficients and estimates of the coefficient on a worker's average number of hours per month. The table displays three specifications: column (3) includes no controls, column (2) includes only time controls, and column (1) includes time controls and additional covariates from the quotes data. Observations are censored at October 2021. All specifications also include a dummy for low hours because panel 3a suggests survival may not be monotonic in hours and to proxy for optimistic misperceptions amongst variable policyholder minimizers. Standard errors are shown in parentheses. The number of observations refers to the number of observations in the stratified data that is used to estimate the time varying coefficients. Covariates are not observed for all drivers so there are fewer observations in the "all controls" column.

Table C2: Cox Proportional Hazards Model with Time-Varying Coefficients

	Dependent variable:			
	Tenure in the gig economy (months)			
	No cover control	No gender control	No age control	No low hours control
	(1)	(2)	(3)	(4)
Mean hours	-0.001^{***}	-0.001^{**}	-0.001^{**}	-0.006^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Minimizer (<= 2 months)	0.179^{*}	0.222^{**}	0.262^{***}	0.181^{*}
	(0.099)	(0.100)	(0.099)	(0.099)
Optimistic (<= 2 months)	0.388^{***}	0.480^{***}	0.535^{***}	0.322^{***}
	(0.103)	(0.104)	(0.104)	(0.104)
Minimizer (> 2 months)	-0.095	-0.053	-0.007	-0.289^{***}
	(0.070)	(0.070)	(0.070)	(0.070)
Optimistic (> 2 months)	0.082	0.172^{**}	0.230^{***}	-0.122
	(0.076)	(0.078)	(0.078)	(0.078)
Low hours	Yes	Yes	Yes	No
Time controls	Yes	Yes	Yes	Yes
Age	Yes	Yes	No	Yes
Gender	Yes	No	Yes	Yes
Cover	No	Yes	Yes	Yes
Observations	23,969	23,969	24,013	23,969
R^2	0.075	0.075	0.073	0.038

Notes: *p<0.1; **p<0.05; ***p<0.01. This table shows estimates from a Cox proportional hazards model with time varying coefficients on the categories variable; the effect of this factor variable is allowed to differ between the first two months of a workers spell and any remaining months. Coefficients reflect percentage changes in the base hazard rate associated with the corresponding variable. The main panel of the table shows estimates for these coefficients and estimates of the coefficient on a workers average number of hours per month. Standard errors are shown in parentheses.

Table C3: Linear Probability Model

	Dependent variable:			
	Tenure <= 2 months		2 < Tenure <= 6 months	
	Controls	No Controls	Controls	No Controls
	(1)	(2)	(3)	(4)
Mean hours	0.0002**	0.0002*	0.0001	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Optimistic	0.083***	0.091***	0.010	0.025***
	(0.010)	(0.009)	(0.010)	(0.009)
Pessimistic	−0.076***	−0.066***	0.076***	0.067***
	(0.020)	(0.021)	(0.020)	(0.020)
Low hours	Yes	Yes	Yes	Yes
Time controls	Yes	No	Yes	No
Age	Yes	No	Yes	No
Gender	Yes	No	Yes	No
Cover	Yes	No	Yes	No
Observations	14,795	15,924	14,795	15,924
R^2	0.163	0.077	0.135	0.009

Notes: *p<0.1; **p<0.05; ***p<0.01. This figure plots the coefficients from an OLS regression, where the outcome is a binary variable that takes value one, if that worker survived for either less than two months—columns (1) and (2)—or between 2 and 6 months—columns (3) and (4). Columns (2) and (4) have no controls, similar to column (3) in figure C1. Columns (1) and (3) control for all available covariates, as in column (1) in figure C1

Table C4: Linear Conditional Probability Model

	Dependent variable:			
	Tenure <= 2 months		2 < Tenure <= 6 months	
	Controls	No Controls	Controls	No Controls
	(1)	(2)	(3)	(4)
Mean hours	0.0002**	0.0002*	0.0003**	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Optimistic	0.083***	0.091***	0.105***	0.125***
	(0.010)	(0.009)	(0.013)	(0.013)
Pessimistic	−0.076***	−0.066***	0.038*	0.049*
	(0.020)	(0.021)	(0.023)	(0.025)
Low hours	Yes	Yes	Yes	Yes
Time controls	Yes	No	Yes	No
Age	Yes	No	Yes	No
Gender	Yes	No	Yes	No
Cover	Yes	No	Yes	No
Observations	14,795	15,924	9,174	9,805
R^2	0.163	0.077	0.263	0.021

Notes: *p<0.1; **p<0.05; ***p<0.01. This figure plots the coefficients from an OLS regression, where the outcome is a binary variable that takes value one, if that worker survived for either less than two months—columns (1) and (2)—or between 2 and 6 months conditional on surviving beyond 2 months—columns (3) and (4). Columns (2) and (4) have no controls, similar to column (3) in figure C1. Columns (1) and (3) control for all available covariates, as in column (1) in figure C1.

show the dynamics of hours before and during the Covid pandemic. Panel C6g shows the baseline figure but without enforcing a balanced panel. Lastly, panel C6h shows the trajectory of hours for third party only policyholders.

Figure 4 shows the dynamics of hours at the weekly level. They can also be displayed at the monthly level—this is done in figure C7. I do this for all three definitions of the categories that I use.

Figure C9 shows responses to the survey of gig workers' experiences for self-reported optimistic and pessimistic workers, respectively. To construct this figure, I subtract the share of responses by minimizers from those of the other categories in order to illustrate the relative prevalence of responses. Moreover, although the differences are not statistically significant, in order to get some reasonable precision I aggregated all the questions asked in the survey about workers experiences. These are questions about earnings, costs, and the difficulty of work. The figure shows that pessimistic workers are most likely to report aspects of gig work are better than they expected. Meanwhile, minimizers are most likely to report experiences as expected. Lastly, optimistic workers most frequently report gig work to be worse than expected.

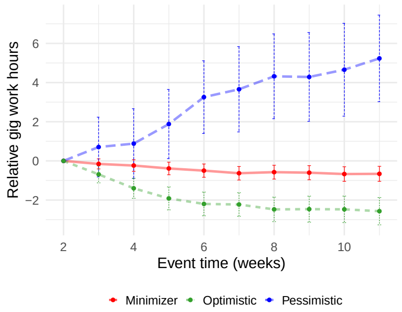
Finally, figure C10 shows the aggregate responses to all experience questions at the finest level of response. There is a tendency to find gig work worse than expected, which is consistent with some evidence of optimism in fixed policy choice and results from the model. However, the majority of the mass falls in the "As expected" and "A little worse" bins, which indicates misperceptions are not too severe—again consistent with the model's results.

Figure C11 shows the distribution of individual break-even points.

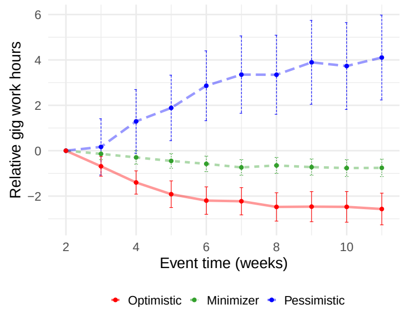
Table C5 presents summary statistics for the worker-level covariates from the quotes data.

Table C6 shows the average level of worker-level covariates within each category.

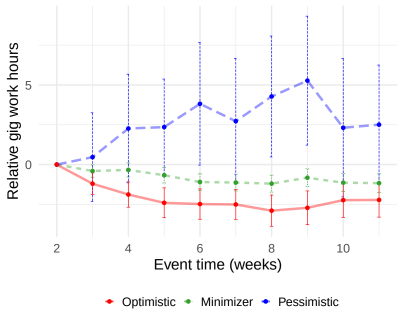
Figure C6: Hours Worked Over Time by Categories for Different Definitions & Samples



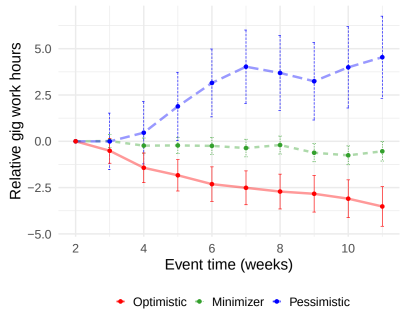
(a) Alternative categories: bill minimization



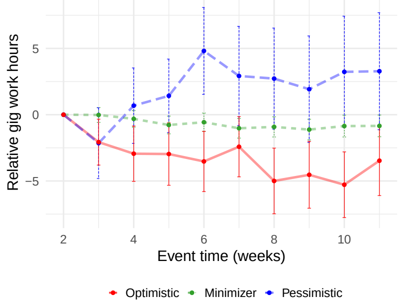
(b) Alternative categories: average hours



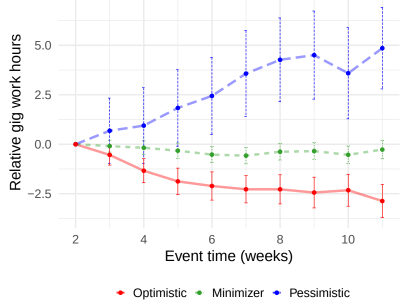
(c) Under 30s



(d) Over 30s



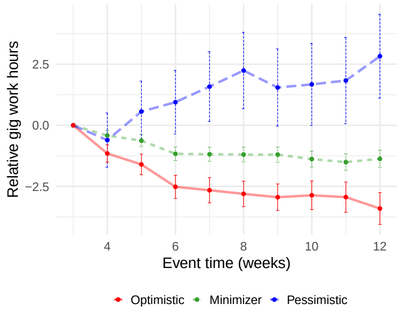
(e) Pre-04/01/202



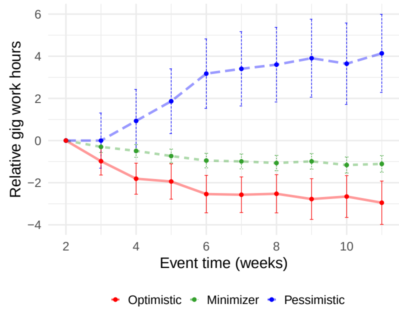
(f) 04/01/2020-06/01/2021

Notes: These figures plot three sets of coefficients from three separate regressions, which are run on a balanced panel (unless otherwise specified) of each category of worker. Weekly hours are regressed on fixed effects and event time dummies, where $t = 2$ corresponds to their second month in the gig economy (*i.e.*, event time is tenure in the gig economy), as well as calendar time controls. Intuitively, each coefficient represents the difference in hours at a given point in time from their hours in their first month in the gig economy. SEs are clustered at the worker level with a HC3 weighting scheme.

Figure C6: Hours Worked Over Time by Categories for Different Definitions & Samples



(g) Not balanced



(h) Third party only

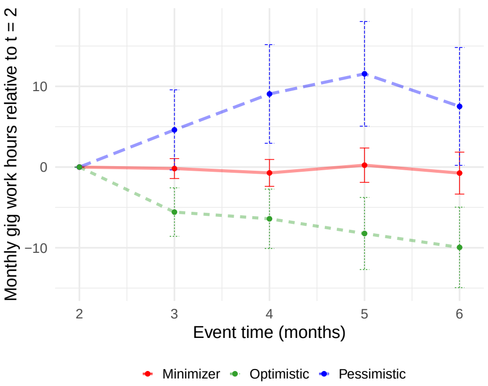
Notes: These figures plot three sets of coefficients from three separate regressions, which are run on a balanced panel (unless otherwise specified) of each category of worker. Weekly hours are regressed on fixed effects and event time dummies, where $t = 2$ corresponds to their second month in the gig economy (*i.e.*, event time is tenure in the gig economy), as well as calendar time controls. Intuitively, each coefficient represents the difference in hours at a given point in time from their hours in their first month in the gig economy. SEs are clustered at the worker level with a HC3 weighting scheme.

Table C5: Worker Covariate Summary Statistics

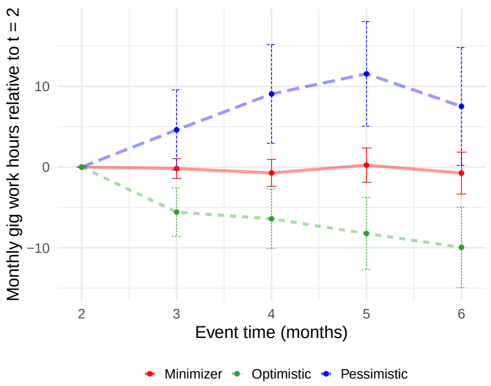
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Age	15,411	32.227	7.811	20	26	31	37	65
Gender	15,440	0.913	0.281	0	1	1	1	1
Cover	16,575	0.813	0.390	0	1	1	1	1
Licence	15,412	5.585	5.991	0	1	3	8	45

Notes: This figure shows summary statistics for worker-level covariates. The gender variable was received as binary and takes value one, if male, and zero otherwise. Cover is coded so that third party coverage takes value one, while fire and theft and comprehensive cover take value zero. The licence variable reports how long a worker has had their licence for.

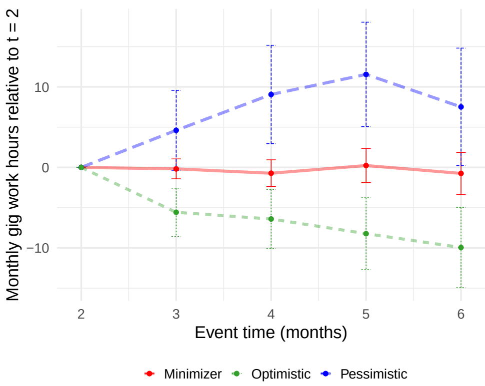
Figure C7: Hours Worked Over Time by Category at a Monthly Frequency



(a) By baseline categories



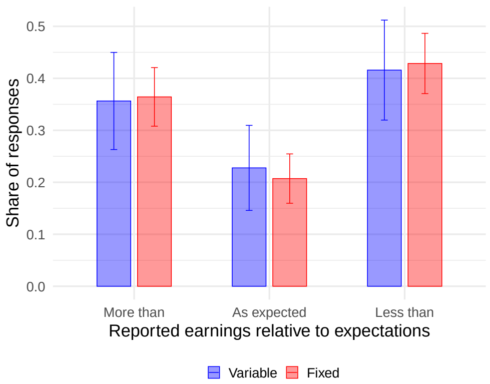
(b) By alternative categories: bill minimization



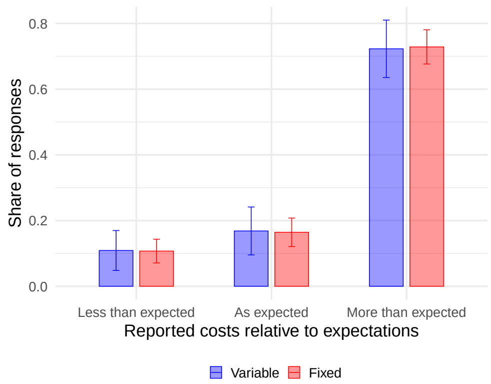
(c) By alternative categories: mean hours

Notes: These figures plot three sets of coefficients from three separate regressions, which are run on a balanced panel of each category of worker. Monthly hours are regressed on fixed effects and event time dummies, where $t = 2$ corresponds to their second month in the gig economy (*i.e.*, event time is tenure in the gig economy), as well as calendar time controls. Intuitively, each coefficient represents the difference in hours at a given point in time from their hours in their first month in the gig economy. SEs are clustered at the worker level with a HC3 weighting scheme.

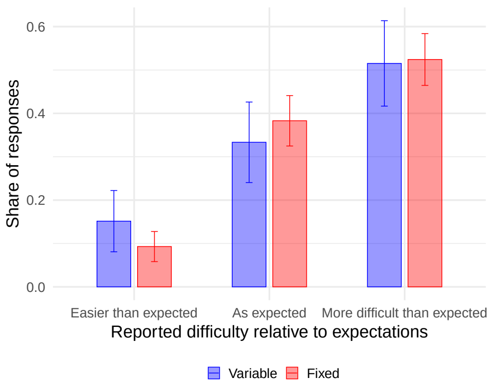
Figure C8: Experiences and Learning



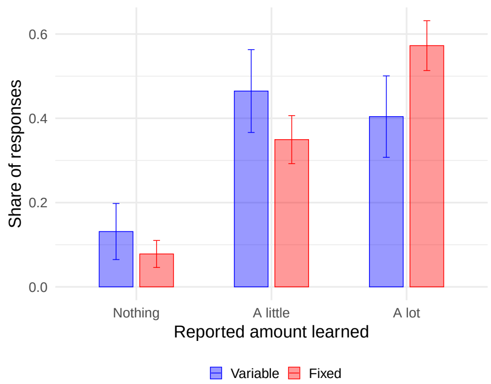
(a) "Are you earning (before costs) more or less than you expected in this job?"



(b) "Are the costs in this job (*e.g.*, fuel, insurance) more or less than you expected?"



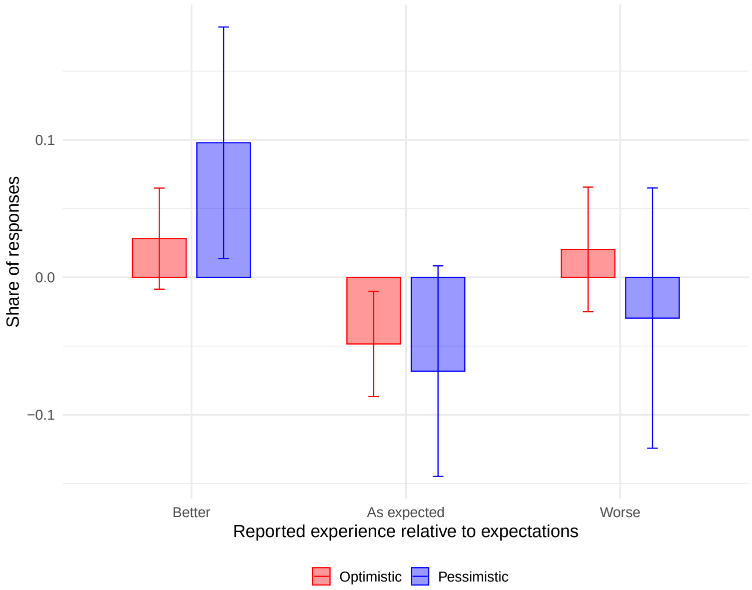
(c) "Is the difficulty of this job more or less than you expected when you started?"



(d) "Have you learned much about the costs vs benefits of this job since you started?"

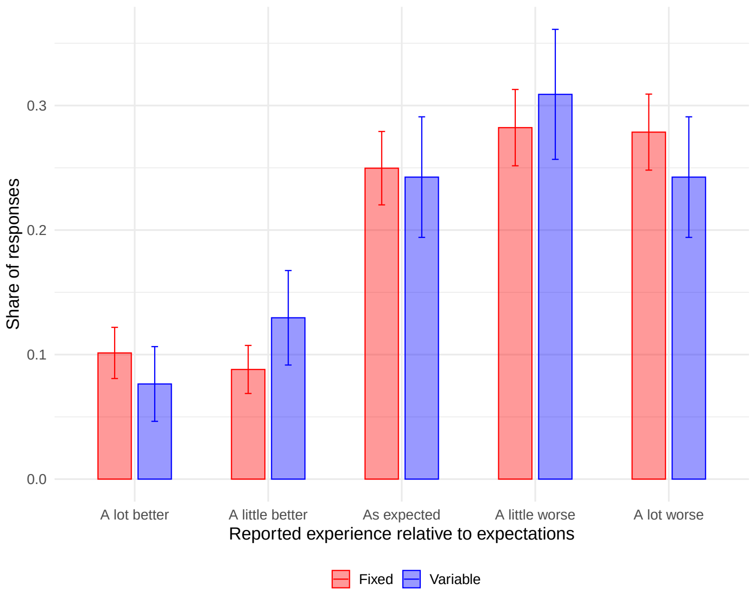
Notes: This figure plots the share of responses to four questions from the survey. The sample contains 85 variable users and 251 fixed users. Standard errors are calculated by applying the law of large numbers to the average of a random variable that follows the multinomial distribution with one trial (*i.e.*, $\sqrt{p_j \cdot (1-p_j)/N}$ where p_j is the share of responses for a given category j and N is the number of observations).

Figure C9: Survey Responses by Category Relative to Minimizers



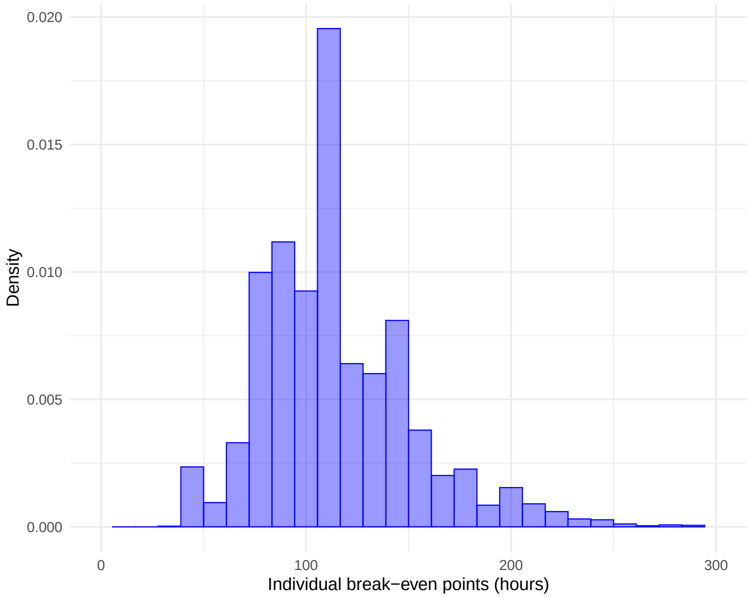
Notes: This figure shows the relative frequency of responses to an aggregate measure of workers' experiences in the gig economy.

Figure C10: Survey Responses by Category Relative to Minimizers



Notes: This figure shows the relative frequency of responses to an aggregate measure of workers' experiences in the gig economy.

Figure C11: Distribution of Break-Even Points



Notes: This figure shows the distribution of individual-level break-even points, which are constructed as a worker's quoted fixed premium divided by the variable premium.

Table C6: Covariates by Categories

Categories	Age	Licence	Cover	Gender
Minimizer	33.00	5.95	0.87	0.93
Optimistic	32.12	5.32	0.50	0.93
Pessimistic	36.88	6.64	1	0.93

Notes: This table shows the average level of worker covariates in each category.

D Learning in the Gig Economy

In this appendix, I show that the functional form for how gig workers learn over time is derived from a micro-founded learning process, where individuals update their priors in a Bayesian fashion as they learn from normally distributed signals. As an example, I do this in the context of taxi drivers who learn about their wage rate.

D.1 The Environment

Drivers receive a signal $w_i + \mu_{i,t}$ about their true wage rate w_i after a week's driving is finished. So for week zero, drivers drive according to their prior $w_{i,0}$. Note that this perceived wage rate also has an associated variance σ_0^2 which forms an exogenous, initial prior $\mathrm{N}(w_{i,0}, \sigma_0^2)$ over the true wage rate w_i. Then, in week one, they update $w_{i,0}$ to $w_{i,1}$ using their prior, the signal, and the variance of the distribution from which the signal is drawn, where $w_i + \mu_{i,t} \sim \mathrm{N}\big(w_i, \sigma_\mu^2\big)$.

Given homoskedastic variance across drivers' priors and signals, the perceived wage rate $w_{i,t}$ and its variance σ_t^2 acquires a convenient form

$$w_{i,t} = \frac{\sigma_\mu^2 + \sigma_0^2}{\sigma_\mu^2 + (t+1)\cdot\sigma_0^2}\cdot w_{i,0} + \frac{t\cdot\sigma_0^2}{\sigma_\mu^2 + (t+1)\cdot\sigma_0^2}\cdot w_i + \frac{\sigma_0^2}{\sigma_\mu^2 + (t+1)\cdot\sigma_0^2}\cdot\sum_{k=0}^{t}\mu_{i,t-k} \tag{19}$$

$$\sigma_t^2 = \frac{\sigma_0^2}{1 + t\cdot\frac{\sigma_0^2}{\sigma_\mu^2}}.$$

Note that the mean of beliefs is a homographic function in time, as is the learning process that I specify in section 4.

To see this, consider the variance of beliefs over time

$$\begin{aligned}
\sigma_1^2 &= \frac{\sigma_\mu^2 \cdot \sigma_0^2}{\sigma_\mu^2 + \sigma_0^2} \\
\sigma_2^2 &= \frac{\sigma_\mu^2 \cdot \sigma_1^2}{\sigma_\mu^2 + \sigma_1^2} \\
&= \frac{\sigma_\mu^2 \cdot \left(\frac{\sigma_\mu^2 \cdot \sigma_0^2}{\sigma_\mu^2 + \sigma_0^2}\right)}{\sigma_\mu^2 + \left(\frac{\sigma_\mu^2 \cdot \sigma_0^2}{\sigma_\mu^2 + \sigma_0^2}\right)} \\
&= \frac{\sigma_0^2}{1 + 2 \cdot \frac{\sigma_0^2}{\sigma_\mu^2}} \\
\sigma_3^2 &= \frac{\sigma_\mu^2 \cdot \left(\frac{\sigma_0^2}{1+2\cdot\frac{\sigma_0^2}{\sigma_\mu^2}}\right)}{\sigma_\mu^2 + \left(\frac{\sigma_0^2}{1+2\cdot\frac{\sigma_0^2}{\sigma_\mu^2}}\right)} \\
&= \frac{\sigma_0^2}{1 + 3 \cdot \frac{\sigma_0^2}{\sigma_\mu^2}} \\
&\vdots \\
\implies \sigma_t^2 &= \frac{\sigma_0^2}{1 + t \cdot \frac{\sigma_0^2}{\sigma_\mu^2}}.
\end{aligned}$$

The variance of beliefs are used to weight signals, and so the mean of beliefs over time look like

$$\begin{aligned}
w_{i,t} &= \frac{\sigma_\mu^2 + t \cdot \sigma_0^2}{\sigma_\mu^2 + (t+1) \cdot \sigma_0^2} \cdot w_{i,t-1} + \frac{\sigma_0^2}{\sigma_\mu^2 + (t+1) \cdot \sigma_0^2} \cdot \left(w_i + \mu_{i,t}\right) \\
&= \frac{\sigma_\mu^2 + t \cdot \sigma_0^2}{\sigma_\mu^2 + (t+1) \cdot \sigma_0^2} \cdot \left(\frac{\sigma_\mu^2 + (t-1) \cdot \sigma_0^2}{\sigma_\mu^2 + t \cdot \sigma_0^2} \cdot w_{i,t-2} + \frac{\sigma_0^2}{\sigma_\mu^2 + t \cdot \sigma_0^2} \cdot \left(w_i + \mu_{i,t-1}\right)\right) \ldots \\
&\ldots + \frac{\sigma_0^2}{\sigma_\mu^2 + (t+1) \cdot \sigma_0^2} \cdot \left(w_i + \mu_{i,t}\right) \\
&\vdots \\
&= \frac{\sigma_\mu^2 + \sigma_0^2}{\sigma_\mu^2 + (t+1) \cdot \sigma_0^2} \cdot \log(w_{i,0}) + \frac{t \cdot \sigma_0^2}{\sigma_\mu^2 + (t+1) \cdot \sigma_0^2} \cdot w_i + \frac{\sigma_0^2}{\sigma_\mu^2 + (t+1) \cdot \sigma_0^2} \cdot \sum_{k=0}^{t} \mu_{i,t-k}.
\end{aligned}$$

D.2 Implications

Taking expectations of equation (19) with respect to signals yields

$$\mathbb{E}\left[w_{i,t}\right] = \frac{\sigma_\mu^2 + \sigma_0^2}{\sigma_\mu^2 + (t+1)\cdot\sigma_0^2}\cdot w_{i,0} + \frac{t\cdot\sigma_0^2}{\sigma_\mu^2 + (t+1)\cdot\sigma_0^2}\cdot w_i.$$

Note that this can be rewritten as

$$\mathbb{E}\left[w_{i,t}\right] = \frac{\lambda}{\lambda+t}\cdot w_{i,0} + \frac{t}{\lambda+t}\cdot w_i.$$

where $\lambda = \frac{\sigma_\mu^2+\sigma_0^2}{\sigma_0^2}$. Thus, the speed of learning parameter λ reflects how noisy the signal is relative to initial aggregate uncertainty. Further, this analysis reveals that λ should be bounded from below by one. In practice, I find that λ is estimated to be close to one, which implies that the signals gig workers receive are precise relative to the variance in initial misperceptions.

Intuitively, the way that learning is modeled in equation (2) is similar to estimating a full model of Bayesian learning, where the agents' signals are simulated. This is because, if a sufficient number of agents were simulated, then averaging over agents with the same initial misperception would lead to (2). Therefore, when using a simulated method of moments estimator, each simulated agent approximates the average behavior of many individuals with the same initial belief.

D.3 Learning Over Multiple Dimensions

In this subsection, I show that learning over multiple dimensions can be approximated with learning about a single parameter. To demonstrate this, I use the example of a net wage w which is made up of a gross wage b and some costs c, so that $w = b - c$. If the wage was a non-linear combination of parameters, then a first-order Taylor approximation could represent w. Maintaining the notation from above but using superscripts to denote references to gross wages and costs, we have

$$\begin{aligned}\mathbb{E}\left[w_{i,t}\right] =& \frac{\bar{\lambda}}{\bar{\lambda}+t}\cdot w_{i,0} + \frac{t}{\bar{\lambda}+t}\cdot w_i + \left(\frac{\lambda^b}{\lambda^b+t} - \frac{\bar{\lambda}}{\bar{\lambda}+t}\right)\cdot b_{i,0} + \left(\frac{t}{\lambda^b+t} - \frac{t}{\bar{\lambda}+t}\right)\cdot b_i \ldots \\ & \ldots + \left(\frac{\lambda^c}{\lambda^c+t} - \frac{\bar{\lambda}}{\bar{\lambda}+t}\right)\cdot c_{i,0} + \left(\frac{t}{\lambda^c+t} - \frac{t}{\bar{\lambda}+t}\right)\cdot c_i,\end{aligned}$$

where $\bar{\lambda} \in \left(\min\{\lambda^b,\lambda^c\}, \max\{\lambda^b,\lambda^c\}\right)$. Therefore, learning over multiple dimensions can be approximated by learning over a single dimension. The accuracy of this approximation is greater when the relative variance of the prior and signal distributions for the two components are similar. Note that this does not restrict the scale of uncertainty on either component.

E Model Derivations

This section provides some additional derivations for analysis conducted in the paper.

E.1 Proposition 22 Hours Thresholds

The thresholds for workers' labor supply rule with hours-qualified benefits are given by

$$\rho_j = \frac{j^{1/\varepsilon} \cdot (p(\omega)+\kappa)}{\hat{\theta}_{i,t}} \text{ for } j = 15, 25,$$

$$\bar{\bar{\rho}}^{\varepsilon} \cdot \left(\frac{1}{\varepsilon - 1} \cdot \frac{\hat{\theta}^{\varepsilon}_{i,t}}{(p(\omega)+\kappa)^{\varepsilon-1}} \right) - \bar{\bar{\rho}} \cdot \left(\hat{\theta}_{i,t} \cdot \frac{25^{1-1/\varepsilon}}{1-1/\varepsilon} \right) + 200 - 400 + \big(p(\omega)+\kappa\big) \cdot 25 = 0,$$

$$\bar{\rho}^{\varepsilon} \cdot \left(\frac{1}{\varepsilon - 1} \cdot \frac{\hat{\theta}^{\varepsilon}_{i,t}}{(p(\omega)+\kappa)^{\varepsilon-1}} \right) - \bar{\rho} \cdot \left(\hat{\theta}_{i,t} \cdot \frac{15^{1-1/\varepsilon}}{1-1/\varepsilon} \right) - 200 + \big(p(\omega)+\kappa\big) \cdot 15 = 0.$$

And to find $\underline{\rho}$

$$\begin{aligned}
(1-\psi)\cdot\nu \le u(15,\omega;\rho_{15}) &\implies (1-\psi)\cdot\nu = u(h^*(\omega),\omega;\underline{\rho}) \\
u(15,\omega;\rho_{15}) < (1-\psi)\cdot\nu \le u(15,\omega;\rho_{15}) + 200 &\implies \underline{\rho} = \rho_{15} \\
u(15,\omega;\rho_{15}) + 200 < (1-\psi)\cdot\nu \le u(25,\omega;\rho_{25}) + 200 &\implies (1-\psi)\cdot\nu = u(h^*(\omega),\omega;\underline{\rho}) + 200 \\
u(25,\omega;\rho_{25}) + 200 < (1-\psi)\cdot\nu \le u(25,\omega;\rho_{25}) + 400 &\implies \underline{\rho} = \rho_{25} \\
u(25,\omega;\rho_{25}) + 400 < (1-\psi)\cdot\nu &\implies (1-\psi)\cdot\nu = u(h^*(\omega),\omega;\underline{\rho}) + 400.
\end{aligned}$$

E.2 Cholesky Decomposition of Variance-Covariance Matrix

$$\begin{pmatrix} \sigma_\theta^2 & \sigma_{\theta,\phi} & \sigma_{\theta,\nu} \\ \sigma_{\phi,\theta} & \sigma_\phi^2 & \sigma_{\phi,\nu} \\ \sigma_{\nu,\theta} & \sigma_{\nu,\phi} & \sigma_\nu^2 \end{pmatrix} = \begin{pmatrix} l_{1,1} & 0 & 0 \\ l_{2,1} & l_{2,2} & 0 \\ l_{3,1} & l_{3,2} & l_{3,3} \end{pmatrix} \times \begin{pmatrix} l_{1,1} & l_{2,1} & l_{3,1} \\ 0 & l_{2,2} & l_{3,2} \\ 0 & 0 & l_{3,3} \end{pmatrix}$$

$$\begin{aligned} \sigma_\theta^2 &= l_{1,1}^2 \\ \sigma_\phi^2 &= l_{2,1}^2 + l_{2,2}^2 \\ \sigma_\nu^2 &= l_{3,1}^2 + l_{3,2}^2 + l_{3,3}^2 \\ \sigma_{\theta,\phi} &= l_{1,1} \cdot l_{2,1} \\ \sigma_{\theta,\nu} &= l_{1,1} \cdot l_{3,1} \\ \sigma_{\phi,\nu} &= l_{2,1} \cdot l_{3,1} + l_{2,2} \cdot l_{3,2}, \end{aligned}$$

where $l_{2,1}$ and $l_{3,2}$ is set equal to zero in order to ensure $\sigma_{\phi,\theta} = 0$ and $\sigma_{\phi,\nu} = 0$.

F List of Empirical Moments

1. The labor market share of this section of the gig economy.
2. The proportion of workers on the variable policy.
3. The mean number of hours worked in a month by workers on the variable policy.
4. The standard deviation of the number of hours worked in a month by workers on the variable policy.
5. The mean number of hours worked in a month by workers on the fixed policy.
6. The standard deviation of the number of hours worked in a month by workers on the fixed policy.
7. The share of variable policy workers who are not on the cost-minimizing policy.
8. The share of fixed policy workers who are not on the cost-minimizing policy.
9. The mean distance between the break-even point and the number of hours worked in a month for non-cost-minimizing variably policy workers.
10. The standard deviation of the distance between the break-even point and the number of hours worked in a month for non-cost-minimizing variably policy workers.
11. The mean distance between the break-even point and the number of hours worked in a month for non-cost-minimizing fixed policy workers.
12. The standard deviation of the distance between the break-even point and the number of hours worked in a month for non-cost-minimizing variably policy workers.
13. The initial hazard rate of cost-minimizing variable policy holders.
14. The initial hazard rate of cost-minimizing fixed policy holders.
15. The initial hazard rate of non-cost-minimizing fixed policy holders.
16. The initial decline in hours per month of non-cost-minimizing variable policy holders.
17. The initial decline in hours per month of non-cost-minimizing fixed policy holders.
18. The mean quoted fixed premium for fixed policy holders.
19. The mean quoted fixed premium for variable policy holders.

20. The standard deviation of quoted fixed premiums for fixed policy holders.
21. The standard deviation of quoted fixed premiums for variable policy holders.
22. The frequency of zero hour months.
23. The average within worker standard deviation in hours.

Appendix References

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