Appendix A: Summary Statistics of Key Variables

Table A1 present summary statistics of the three key variables in our analysis: offer, income so far (ISF), and hours so far (HSF). We normalize the offer variable to the minimum offer due to confidentiality.

Table A1 Summary statistics of key variables: offer (relative to minimum offer), ISF, and HSF

	SUV				Sedan			
	Midday	PM peak	PM off-peak	Late night	Midday	PM peak	PM off-peak	Late night
Offer Q1	2.1	2.27	2.03	2.05	1.79	1.71	1.73	1.73
Offer Median	2.8	2.33	2.21	2.21	2.13	1.9	1.9	1.9
Offer Mean	2.73	2.39	2.28	2.34	2.17	1.97	2	2
Offer Q3	3.33	2.37	2.36	2.5	2.62	2.1	2.11	2.2
ISF Q1	0	0	0	0	0	0	0	0
ISF Median	0	0	0	0	0	0	0	0
ISF Mean	17.3	84.5	106	110	3.91	31.1	23.4	33.3
ISF Q3	0	124.3	173	188	0	0	0	0
HSF Q1	0	0	0	0	0	0	0	0
HSF Median	0	0	0	0	0	0	0	0
HSF Mean	0.401	2	2.62	2.75	0.125	0.999	0.731	1.07
HSF Q3	0	3.04	4.54	5	0	0	0	0

Appendix B: Additional Details of the Main Results

Tables B2 and B3 display our estimates for the Midday shift of SUV and sedan drivers, respectively. The first column in each table reports the estimates from the control function probit of the choice equation. The second column reports the estimates from the baseline OLS for the level equation replicating the model implemented in the literature (Camerer et al. 1997, Sheldon 2016). We follow the model specification and IV strategy used in past work. Covariates include log hourly wage, temperature, rain indicator, day of week, and month dummies and we use the average of other drivers' hourly wages as an instrument. We then present the estimates from the level equation of the two-part model in the third column, and from the level equation of our main model in the fourth column.

Table B2 Estimates of two-stage selection models of SUV drivers' decisions during Midday shifts

	Choice Eq *Control Function*	*Level Eq* *Baseline*	*Level Eq* *Two-Part*	*Level Eq* *Main Model*
Incentives/targets				
Offer/Earnings	0.002^{***} (0.0006)	-0.083^{***} (0.019)	0.001 (0.001)	0.001 (0.001)
Income so far	-0.017^{***} (0.004)	-	-0.009^{***} (0.002)	-0.008^{***} (0.002)
Hours so far	2.904^{***} (0.163)	-	1.690^{***} (0.068)	1.826^{***} (0.070)
Hours last week				
Total	0.017^{***} (0.0003)	-	-	-
Same shift	-	-	0.056^{***} (0.002)	0.059^{***} (0.002)
New driver	0.590^{***} (0.060)	-	-	-
IMR	-	-	-	0.271^{***} (0.029))
Observations	124,769	45,330	45,329	45,329
R^2	-	0.378	0.552	0.552

Note: *p<0.05; **p<0.01; ***p<0.001

SUV drivers. For the choice equation, we find that hourly financial offer and cumulative work hours have a significantly positive impact on the decision to work, while cumulative earnings have a significantly negative impact. The first effect indicates that drivers respond positively to an increase in financial incentives as predicted by the standard income effect. The positive effect of HSF suggests that drivers who have worked for a longer period of time during the preceding shift (e.g., AM Peak), controlling for other covariates, are more likely to work for a new shift (e.g., Midday). We refer to this behavior as *inertia*, which we will discuss further as it becomes more prevalent across different analyses. In contrast, the negative effect of ISF reflects a potential income-targeting behavior, that is, drivers are less likely to work if they have earned more income or become closer to their (unobserved) income target. We also find that the number of hours each driver worked in the previous week has a significant positive impact on the decision to work. This could suggest that drivers tend to stick to their work patterns and hold relatively stable work schedules, as observed in Chen et al. (2019). In other words, past work decisions could play an important role in how drivers form and adjust their income and time targets. Lastly, we observe that newer drivers who recently joined the platform are significantly more likely to work.

We next consider the level equation of work duration. Interestingly, under the baseline model, we observe that SUV drivers exhibit a negative income elasticity, similar to full-time taxi drivers investigated in Camerer et al. (1997) and Thakral and Tô (2021), rather than a positive income elasticity observed for ride-hailing drivers (Sheldon 2016). For the other two models in which we incorporate proxies for income and time targets, the estimates for the level equation are relatively consistent regardless of sample selection correction. We observe a directional positive impact of hourly earnings on work duration, providing additional evidence that drivers exhibit positive income elasticity. The impact of ISF is significantly negative, suggesting that income-targeting behavior also negatively affects work duration. On the other hand, the impact of HSF or inertia behavior is significantly positive. We again observe that drivers might stick to their schedules as the work duration for the focal shift is positively affected by the work duration during the same shift in the previous week. In addition, the estimated coefficient of our sample selection correction variable (IMR) is statistically significant, confirming that selection into working is not random. Overall, we observe that the positive effects of hourly earnings and HSF dominate the negative impact of ISF on the work duration.

Sedan drivers. We perform the same estimation and obtain similar results for sedan drivers: hourly offer or earnings rate and HSF have a positive impact on the decision to work and on the work duration. Under the baseline approach, we observe that, for sedan drivers, (log) hourly earnings rate positively affects the number of hours worked. The positive income elasticity is in line with findings from ride-hailing drivers in Sheldon (2016). This may suggest that SUV and sedan drivers are fundamentally different types of workers: SUV drivers' behaviors are similar to full-time professional taxi drivers, whereas sedan drivers' behaviors are similar to average drivers on ride-hailing platforms. While descriptive statistics suggest that SUV drivers tend to drive more often and for longer periods relative to sedan drivers, both types of drivers exhibit similar responses to hourly incentive, cumulative earnings, and work hours. Note that the estimated coefficient for IMR is not statistically significant (at $p = 0.05$) for this shift, suggesting that the evidence of selection of bias is weak. Nevertheless, our insights remain valid as the estimates are consistent regardless of sample selection correction. Furthermore, IMR estimates are statistically significant for all the other shifts.

Table B3 **Estimates of two-stage selection models of sedan drivers' decisions during Midday shifts**

	Choice Eq *Control Function*	*Level Eq* *Baseline*	*Level Eq* *Two-Part*	*Level Eq* *Main Model*
Incentives/targets				
Offer/Earnings	0.007*** (0.0008)	0.080*** (0.028)	0.001 (0.001)	0.001 (0.001)
Income so far	−0.031*** (0.006)	-	−0.007*** (0.002)	−0.007*** (0.002)
Hours so far	3.243*** (0.192)	-	1.073*** (0.058)	1.058*** (0.061)
Hours last week				
Total	0.022*** (0.0004)	-	-	-
Same shift	-	-	0.079*** (0.003)	0.078*** (0.003)
New driver	0.660*** (0.042)	-	-	-
IMR	-	-	-	-0.029 (0.029)
Observations	113,444	20,307	20,297	20,297
R^2	-	0.389	0.580	0.580

Note: *p<0.05; **p<0.01; ***p<0.001

Figures B1 and B2 provide additional details of the main results from our two-stage model of drivers' decisions across shifts and across days, respectively. For each of the key variables, we provide the estimated coefficient and the standard error in parenthesis. Within each model, we also report the estimated coefficient and the standard error for IMR and two R^2 values, total R^2 (top) and within R^2 (bottom, italicized). We acknowledge that a few of the IMR estimates are not statistically significant, suggesting that the selection bias is weak in some cases. However, our insights regarding the impact of financial incentives, cumulative income, and cumulative work hours on the decisions of both stages are consistent across different model specifications and selection approaches (e.g., two-part model and Dahl's correction).

Figure B1 **Estimates of our two-stage model of drivers' shift-level decisions across different shifts**

	Choice (Work or not)				**Level** (How long)					
SUV	Offer	ISF	HSF	N	Earn	ISF	HSF	IMR	R^2	N
Midday	**0.0024 (0.0006)**	**-0.0173 (0.0036)**	**2.9044 (0.1632)**	124,769	0.001 (0.001)	**-0.008 (0.002)**	**1.826 (0.070)**	**0.271 (0.029)**	0.552 *0.239*	45,329
PM-Peak	**0.0082 (0.0016)**	**-0.0022 (0.0002)**	**0.5102 (0.0082)**	131,910	**0.023 (0.005)**	**-0.0004 (0.0001)**	**0.316 (0.009)**	**0.627 (0.043)**	0.244 *0.092*	39,592
PM-OPeak	**0.0018 (0.0008)**	**-0.0024 (0.0001)**	**0.3436 (0.0048)**	130,651	**0.003 (0.001)**	**-0.0001 (0.00003)**	**0.020 (0.002)**	0.009 (0.011)	0.281 *0.029*	26,699
Late Night	**0.0035 (0.0010)**	**-0.0024 (0.0001)**	**0.2817 (0.0047)**	125,382	**0.025 (0.002)**	-0.0002 (0.0001)	**0.022 (0.011)**	-0.088 (0.054)	0.296 *0.027*	17,137
Sedan	Offer	ISF	HSF	N	Earn	ISF	HSF	IMR	R^2	N
Midday	**0.0068 (0.0008)**	**-0.0309 (0.0056)**	**3.2429 (0.1916)**	113,444	0.001 (0.001)	**-0.007 (0.002)**	**1.058 (0.061)**	-0.029 (0.029)	0.580 *0.206*	20,297
PM-Peak	**0.0109 (0.0019)**	**-0.0014 (0.0004)**	**0.4852 (0.0133)**	117,152	**0.020 (0.004)**	**-0.001 (0.0002)**	**0.116 (0.009)**	**-0.120 (0.034)**	0.273 *0.014*	19,613
PM-OPeak	**0.0031 (0.0010)**	**-0.0028 (0.0003)**	**0.4133 (0.0090)**	124,611	**0.003 (0.0005)**	**-0.0002 (0.00004)**	**0.005 (0.002)**	**-0.098 (0.007)**	0.252 *0.029*	17,025
Late Night	0.0018 (0.0014)	**-0.0021 (0.0002)**	**0.3356 (0.0082)**	124,280	**0.036 (0.004)**	**-0.001 (0.0002)**	**0.063 (0.011)**	**-0.378 (0.048)**	0.304 *0.026*	15,623

Note: Solid background with bolded text: significantly positive, striped with bolded text: significantly negative, white with italicized text: non-significant. All at $p = 0.05$.

Figure B2 Estimates of our two-stage model of drivers' day-level decisions across different days

	Choice (Work or not)				**Level** (How long)					
SUV	Offer	ISF	HSF	N	Earn	ISF	HSF	IMR	R^2	N
Tuesday	0.0039 (0.0021)	0.0006 (0.0003)	**0.0581** **(0.0137)**	28,883	-0.003 (0.010)	-0.001 (0.001)	0.027 (0.029)	**-1.711** **(0.184)**	0.422 *0.037*	9,482
Wednesday	0.0036 (0.0020)	**0.0005** **(0.0002)**	**0.0461** **(0.0087)**	21,965	-0.001 (0.008)	-0.0003 (0.0005)	0.028 (0.021)	**-1.274** **(0.192)**	0.422 *0.040*	10,120
Thursday	**0.0087** **(0.0019)**	**0.0005** **(0.0001)**	**0.0358** **(0.0061)**	29,233	-0.006 (0.008)	-0.0004 (0.0003)	**0.042** **(0.014)**	**-0.973** **(0.217)**	0.412 *0.046*	9,894
Friday	**0.0069** **(0.0019)**	0.00001 (0.0001)	**0.0506** **(0.0046)**	20,294	0.013 (0.008)	-0.0004 (0.0002)	**0.055** **(0.012)**	0.007 (0.229)	0.436 *0.031*	9,283
Saturday	**-0.0246** **(0.0036)**	-0.0002 (0.0001)	**0.0292** **(0.0038)**	15,788	-0.002 (0.030)	0.0001 (0.0003)	-0.013 (0.017)	**-2.149** **(0.640)**	0.398 *0.045*	4,372
Sunday	**-0.0216** **(0.0034)**	**-0.0006** **(0.0001)**	**0.0504** **(0.0040)**	13,025	**0.049** **(0.024)**	0.00005 (0.0004)	-0.032 (0.021)	**-3.102** **(0.580)**	0.390 *0.040*	3,240
Sedan	Offer	ISF	HSF	N	Earn	ISF	HSF	IMR	R^2	N
Tuesday	**0.0216** **(0.0028)**	0.0008 (0.0007)	**0.0766** **(0.0221)**	21,283	**-0.040** **(0.015)**	-0.002 (0.002)	**0.070** **(0.035)**	**-0.940** **(0.141)**	0.564 *0.097*	4,681
Wednesday	**0.0128** **(0.0027)**	**0.0016** **(0.0004)**	**0.0435** **(0.0142)**	23,280	0.015 (0.012)	**-0.002** **(0.001)**	**0.122** **(0.023)**	**-0.657** **(0.150)**	0.567 *0.114*	5,278
Thursday	**0.0115** **(0.0026)**	**0.0010** **(0.0003)**	**0.0351** **(0.0095)**	19,982	-0.002 (0.011)	-0.00004 (0.0005)	**0.052** **(0.016)**	-0.254 (0.164)	0.542 *0.100*	5,081
Friday	**0.0173** **(0.0024)**	**0.0004** **(0.0002)**	**0.0375** **(0.0068)**	18,418	-0.009 (0.011)	-0.00002 (0.0004)	**0.026** **(0.013)**	-0.321 (0.209)	0.533 *0.067*	4,666
Saturday	0.0035 (0.0049)	-0.0003 (0.0002)	**0.0502** **(0.0062)**	15,762	-0.006 (0.028)	-0.0002 (0.0004)	**0.038** **(0.014)**	-0.066 (0.311)	0.514 *0.067*	3,817
Sunday	-0.0081 (0.0046)	**-0.0007** **(0.0002)**	**0.0626** **(0.0063)**	12,602	**0.058** **(0.022)**	**-0.001** **(0.0004)**	**0.062** **(0.015)**	-0.317 (0.342)	0.560 *0.101*	3,065

Note: Solid background with bolded text: significantly positive, striped with bolded text: significantly negative, white with italicized text: non-significant. All at $p = 0.05$.

Figures B3 provides the effect sizes for an average driver at the shift and day levels, respectively, under one of the following conditions: (i) a \$10 increase in hourly offer or earning rate, (ii) a \$10 increase in ISF, and (iii) an additional hour to HSF.

Figure B3 Effect sizes of changes in hourly financial offer, ISF, and HSF on drivers' shift-level decisions

	Change in P(Work) (percentage points)					Change in Duration (minutes)				
SUV	Mean	+1% Offer	+1% ISF	+1% HSF	N	Mean	+1% Offer	+1% ISF	+1% HSF	N
Midday	0.343	**0.079**	**-0.152**	**0.541**	124,769	4.987	*0.026*	**-0.239**	**1.216**	45,329
PM-Peak	0.277	**0.078**	**-0.064**	**0.348**	131,910	2.421	**0.726**	**-0.056**	**1.054**	39,592
PM-OPeak	0.182	**0.049**	**-0.051**	**0.178**	130,651	0.731	**0.057**	**-0.027**	**0.095**	26,699
Late Night	0.117	**0.031**	**-0.031**	**0.093**	125,382	1.996	**0.484**	-0.023	**0.077**	17,137
Sedan	Mean	+1% Offer	+1% ISF	+1% HSF	N	Mean	+1% Offer	+1% ISF	+1% HSF	N
Midday	0.137	**0.034**	**-0.034**	**0.117**	113,444	4.186	*0.026*	**-0.114**	**0.549**	20,297
PM-Peak	0.123	**0.045**	**-0.007**	**0.080**	117,152	2.327	**0.311**	**-0.075**	**0.312**	19,613
PM-OPeak	0.099	**0.031**	**-0.015**	**0.068**	124,611	0.803	**0.035**	**-0.020**	**0.021**	17,025
Late Night	0.071	*0.033*	**-0.011**	**0.054**	124,280	2.167	**0.579**	**-0.153**	**0.220**	15,623

Note: Solid background with bolded text: significantly positive, striped with bolded text: significantly negative, white with italicized text: non-significant. All at $p = 0.05$.

Appendix C: Alternative Empirical Approaches

C.1. Sample Selection Bias: Dahl's Correction

Following Dahl (2002) and Bray et al. (2019), we use the selection probability as a sufficient statistic for the selection bias. Since, in our context, the choice for each driver is only binary: to work or not, we do not suffer from the curse of dimensionality. Revisiting our level equation (Equation (7)),

$$f(Hour_{i,t}) = \beta_{0,i} + \beta_{\tilde{w}}\tilde{w}_{i,t} + \beta_{ISF}ISF_{i,t} + \beta_{HSF}HSF_{i,t} + \beta\mathbf{Z_{i,t}} + \theta\lambda_{i,t} + u_{i,t},$$

we can substitute IMR (λ) with all basis functions of a B-spline by using the quantiles of work probabilities for all drivers, $\mathbf{P_{work}} = [P(Drive_{i,t} = 1|\mathbf{X_{i,t}}), \forall i]$ as interior knots. Let $\mathfrak{B}(\mathbf{P_{work}}, j)$ be the j^{th} basis function of a degree n B-spline with the quantiles of $\mathbf{P_{work}}$ as m interior knots. Also, we define $\eta_{i,t} = u_{i,t} - \sum_{j=0}^{m+n}\gamma_j\mathfrak{B}(\mathbf{P_{work}}, j)$ to maintain the orthogonality of the error term and the expected hours worked. Thus, our level equation under this approach becomes:

$$f(Hour_{i,t}) = \beta_{0,i} + \beta_{\tilde{w}}\tilde{w}_{i,t} + \beta_{ISF}ISF_{i,t} + \beta_{HSF}HSF_{i,t} + \beta\mathbf{Z_{i,t}} + \sum_{j=0}^{m+n}\gamma_j\mathfrak{B}(\mathbf{P_{work}}, j) + \eta_{i,t}. \qquad \text{(C1)}$$

In Figure C4, we present the estimates for the level equation when choosing $m = n = 3$. Our results remain consistent under both approaches for sample selection correction. Note that, for all but sedan drivers' decisions on Friday and Saturday, the selection variables are significant at $p = 0.05$, hence confirming that there exists a selection bias in the decision to work.

Figure C4 Estimates for the level equation using Dahl's correction

	SUV Drivers			Sedan Drivers		
Shift	Earning	ISF	HSF	Earning	ISF	HSF
Midday	**+**	*+*	**+**	**+**	*+*	**+**
PM-Peak	*+*	**-**	**+**	**+**	**-**	**+**
PM-OPeak	**+**	**-**	**+**	**+**	**-**	**+**
Late Night	**+**	**-**	**+**	**+**	**-**	**+**

	SUV Drivers			Sedan Drivers		
Day	Earning	ISF	HSF	Earning	ISF	HSF
Tue	*-*	*-*	*+*	*-*	*-*	*+*
Wed	*+*	*-*	*+*	**+**	**-**	**+**
Thu	*-*	*-*	*+*	*+*	*+*	*+*
Fri	*-*	**-**	*+*	*-*	*+*	*+*
Sat	**-**	*+*	**-**	*-*	*+*	**-**
Sun	*-*	**+**	**-**	*+*	**-**	**+**

Note: Solid background with bolded **"+"**: significantly positive, striped with bolded **"-"**: significantly negative, white with italicized text: non-significant. All at $p = 0.05$.

C.2. Alternative Instrumental Variables for *Offers*

Co-skippers IV. This IV follows a similar idea to our main IV, but instead of matching drivers based on their past work decisions at a specific time in the past, we now match drivers based on the level of past inactivity. For every day in our data, we categorize drivers into four groups based on each quartile of the number of consecutive days they have been inactive. We call the drivers of a different vehicle type who belong to the same group *co-skippers*. This IV satisfies the *relevance condition:* Since both the focal driver and their co-skippers have been inactive for approximately the same time, their incentives should be highly correlated. From the first stage of our IV estimation, the estimate for the instrument is consistently signifiant and F-statistics across all models except one are larger than the conventional threshold of 10. This

IV also satisfies the *exclusion restriction:* Current incentives for co-skippers should not directly influence the focal driver's work decision because (i) they drive different vehicle types and (ii) the focal driver does not have access to co-skippers' incentives information. The estimates from shift- and day-level analyses are consistent with our main results. Figure C5 presents the signs and statistical significance (at $p = 0.05$) of the estimates across shifts and days. However, these models are outperformed by our main model both in terms of in-sample and out-of-sample accuracy.

Figure C5 Estimates across shifts and days using the co-skippers IV

	Choice (Work or not)				Level (How long)			
SUV	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Midday	433.1	+	**+**	+	266.8	**+**	+	**+**
PM-Peak	289.5	**-**	**-**	**+**	58.7	+	**-**	**+**
PM-OPeak	260.2	**+**	**-**	**+**	45.1	**+**	**-**	**+**
Late Night	329.9	**+**	**-**	**+**	36.4	**+**	**-**	**+**
Sedan	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Midday	229.2	**+**	**+**	**+**	104.4	**+**	+	**+**
PM-Peak	231.3	+	**-**	**+**	31.8	+	**-**	**+**
PM-OPeak	255.9	**+**	**-**	**+**	24.3	**+**	**-**	**+**
Late Night	270.0	**+**	**-**	**+**	30.9	**+**	**-**	**+**

	Choice (Work or not)				Level (How long)			
SUV	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Tuesday	37.9	-	**+**	**+**	21.1	-	**-**	+
Wednesday	41.3	**+**	+	**+**	25.5	-	-	+
Thursday	67.9	**+**	-	**+**	43.9	**-**	+	+
Friday	67.5	**+**	**+**	**+**	41.9	-	-	+
Saturday	89.1	**+**	+	**+**	19.4	**-**	+	-
Sunday	82.1	**-**	**-**	**+**	16.0	**+**	**+**	**-**
Sedan	IV-F	Offer	ISF	HSF	IV-F	Earning	ISF	HSF
Tuesday	25.3	+	+	+	8.8	-	-	+
Wednesday	24.9	**+**	**+**	+	10.6	+	**-**	**+**
Thursday	43.9	**+**	**+**	+	15.8	+	-	+
Friday	39.9	**+**	**+**	**+**	13.6	-	+	-
Saturday	58.3	**+**	+	**+**	12.8	-	+	**-**
Sunday	48.7	-	**-**	**+**	12.5	+	**-**	**+**

Note: Solid background with bolded "+": significantly positive, striped with bolded "-": significantly negative, white with italicized text: non-significant. All at $p = 0.05$.

Hausman-type IV. Inspired by previous studies such as Sheldon (2016), we use the average hourly offer rate received by all other registered drivers during the same shift on the same day as an instrument for the offer rate. Similarly, we use the average hourly earning rate earned by all other active drivers during the same shift on the same day as an instrument for the hourly earning rate. These instruments can be thought of as a mutual offer or earning rate for eligible drivers in New York City at a particular time. In addition, the incentives offered to other drivers should not directly influence the focal driver's decision to work. Controlling for weather and market conditions using the TLC data, we rule out potential confounders that affect both the variation in incentives and in labor decisions. Recall that unlike other ride-hailing platforms, drivers on our platform do not compete with other drivers for promotions as both the base and promotional rates are decided and announced ahead of time. Moreover, promotions are not offered as a way to relocate drivers to high-demand areas (see §3.3 for more details). Thus, it suggests that this IV satisfies the exclusion restriction. The results we obtained using this IV are qualitatively similar to our main results. While this type of IV appears to be valid for the choice equation, low F-statistics suggest that it is a relatively weaker IV relative to both the co-workers and co-skippers IVs.

C.3. Addressing the Multicollinearity Concern

Correlations between ISF and HSF in our data range between 0.667 and 0.928, depending on the time of the day and the vehicle type. While these correlations appear to be on a high side, we gain sufficient statistical power by leveraging our large sample size. Based on Mason and Perreault Jr (1991), our levels of collinearity are between Levels II and III. Given that our R^2 is between 0.25 and 0.5, the minimum sample size of 300 is required. In our case, this requirement is readily satisfied since we have over 100,000 observations for each vehicle type and shift.

Nevertheless, we consider alternative model specifications that still allow us to investigate both the impact of ISF and HSF on the labor decisions. For conciseness, we present two major approaches and a model comparison below. The insights remain valid in all specifications.

C.3.1. Localized hazard regressions. Motivated by Thakral and Tô (2021), we estimate additional models when controlling for drivers who either had the same amount of accumulated earnings or the same amount of time worked so far. Such a specification allows for a flexible, driver-specific hazard of stopping and a time-dependent relationship between each of the covariates and the stopping probability. After driving t trips and accumulating y_{int} from working a total of h_{int} hours, driver i decides to end shift n when the cost of additional effort exceeds the expected continuation value. The variables y_{int} and h_{int} represent income so far (ISF) and hours so far (HSF) in our setting. We let d_{int} be the decision to stop working after trip t in shift n. Thakral and Tô (2021) models the probability that driver i ends shift n at trip t by

$$\mathbb{P}(d_{int}=1) = f(h_{int}) + \beta(h_{int})y_{int} + X_{int}\gamma(h_{int}) + \mu_i(h_{int}) + \epsilon_{int},$$

where $f(\cdot)$ represents the baseline hazard and μ absorbs differences in drivers' baseline stopping tendencies. HSF affects the stopping probability through the baseline hazard and the impact of ISF, covariates, and drivers' fixed effects. $\beta(h)$ reflects the effect of an additional dollar of ISF on the probability of ending a shift for a driver after h hours of work ($HSF = h$). Thakral and Tô (2021) employs local linear regressions to estimate the baseline hazard and the time-varying coefficients by solving a separate weighted least squares problem:

$$\min_{\alpha,\beta,\gamma,\mu_i} \sum_{i,n,t} w(h_{int}-h)(d_{int} - (\alpha h_{int} + \beta y_{int} + X_{int}\gamma + \mu_i))^2$$

with weights given by $w(\cdot)$. With uniform weights, this procedure is equivalent to fitting a linear model to a localized subset of data. We consider time windows of different intervals: 10, 15, 20, 30, and 60 minutes.

Specifically, we consider the following two models:

(i) *HSF impacts how ISF affects the stopping probability.* This is similar to the model formulated in Thakral and Tô (2021). We model the probability that driver i stops working at time t of day n after earning ISF_{int} and spending HSF_{int} hours working for the day as:

$$\mathbb{P}(d_{int}=1) = f(HSF_{int}) + \beta^{w}(HSF_{int})w_{int} + \beta^{ISF}(HSF_{int})ISF_{int} + X_{int}\gamma(HSF_{int}) + \mu_i(HSF_{int}) + \epsilon_{int},$$

where w_{int} is the hourly financial incentive offered at time t of day n. We include the hourly incentive to match our main models and reflect the possibility that drivers are less likely to quit if the current offer is appealing. The local regressions are done by controlling for drivers who were still active at the population median of HSF.

(ii) *ISF impacts how HSF affects the stopping probability.* This model is to validate our findings that drivers exhibit inertia, affecting their work decisions. Using the notation from our setting, we model the probability that driver i stops working at time t of day n after earning ISF_{int} and spending HSF_{int} hours working for the day as:

$$\mathbb{P}(d_{int}=1)=f(ISF_{int})+\beta^{w}(ISF_{int})w_{int}+\beta^{HSF}(ISF_{int})HSF_{int}+X_{int}\gamma(ISF_{int})+\mu_i(ISF_{int})+\epsilon_{int}.$$

The local regressions are estimated by controlling for drivers who were still active when earning cumulative income of the population median of ISF.

Results for Model (i): Impact of ISF. The median number of hours that drivers worked on non-holiday weekdays is 6.72 for SUV drivers and 6.58 for sedan drivers. Table C4 presents the estimates for the local probit models of the decision to quit within 10, 15, 30, or 60 minutes after reaching the population median HSF. The results confirm that financial incentives decrease the quitting probability, while cumulative earnings tend to increase the quitting probability. Under the assumption that cumulative hours worked (HSF) only affect the quitting probability through the impact of offers and ISF, we confirm that income targeting exists while drivers appear to have a positive income elasticity.

Table C4 **Estimates of local probit models of quitting decision controlling for cumulative work hours (HSF)**

Quit within	SUV		Sedan	
	Offer	ISF	Offer	ISF
10 mins	-0.0174	0.0004	-0.0340	0.0025
15 mins	-0.0199^{*}	0.0014	-0.0365^{*}	0.0040^{*}
30 mins	-0.0204^{**}	0.0023^{*}	-0.0321^{**}	0.0039^{**}
1 hour	-0.0047	0.0011	-0.0165	0.0016
Note:	*p<0.05; **p<0.01; ***p<0.001			

Results for Model (ii): Impact of HSF. We perform a similar analysis where we assume that the impact of ISF is only through the varying impact of HSF. The median cumulative earnings drivers made on non-holiday weekdays are $219.73 for SUV drivers and $199.01 for sedan drivers. Table C5 shows that significant inertia is observed among SUV and sedan drivers when the time window of quitting decision is between 10 and 30 minutes. We also find that the hourly financial offer consistently decreases the stopping probability except for SUV drivers where the effect is the opposite.

Table C5 **Estimates of local probit models of quitting decision controlling for cumulative earnings (ISF)**

Quit within	SUV		Sedan	
	Offer	HSF	Offer	HSF
10 mins	-0.18	-0.0652	-0.0047	0.0349
15 mins	-0.0252^{***}	-0.1003^{***}	-0.0091	0.0019
30 mins	-0.0186^{***}	-0.0718^{***}	-0.021^{***}	-0.1103^{***}
1 hour	-0.0202^{**}	-0.0235	-0.0182^{***}	0.0228
Note:	*p<0.05; **p<0.01; ***p<0.001			

C.3.2. Dropping ISF from the estimation. To further showcase that our results are robust and not driven by the multicolinearity between ISF and HSF, we conduct additional analyses when we only include one of the two variables in the estimation. Table C6 shows the estimated coefficients of HSF in our original model compared to the models in which we drop the ISF variable. We show that by excluding ISF from the model, we still find the positive impact of HSF on workers' decisions, suggesting that, while there may exist a positive bias, HSF alone still has a positive impact.

Table C6 Estimates of $\hat{\beta}_{HSF}$ for shift-level estimation for (i) our full model with both ISF and HSF and (ii) model with HSF only

		Sedan		SUV	
		Full	HSF only	Full	HSF only
Midday	Choice	3.2429***	2.212277***	2.9044***	2.138632***
	Level	1.058***	0.851***	1.826***	1.477***
PM-Peak	Choice	0.4852***	0.439504***	0.5102***	0.416586***
	Level	0.116***	0.017***	0.316***	0.273***
PM-OffPeak	Choice	0.4133***	0.323390***	0.3436***	0.245800***
	Level	0.005***	0.001	0.020***	0.016***
Late Night	Choice	0.3356***	0.269243***	0.2817***	0.187992***
	Level	0.063***	0.022**	0.022***	0.012+
Note:	+p<0.1, *p<0.05; **p<0.01; ***p<0.001				

C.3.3. Model comparison. In addition, we compare three model specifications: our model with ISF and HSF, a model without ISF, and a model without HSF. Tables C7 and C8 below present the key performance metrics in our model comparison. We show that our full model is almost always the best performing model both for in-sample fitting and out-of-sample prediction.

C.4. Alternative Construction of ISF and HSF

We first argue that our assumption that the progress toward a daily income or time goal is reset at midnight is reasonable. 91.07% of drivers' working days observed in our data do not overlap with midnight (e.g., they did not work overnight). Furthermore, 99.93% started working between 5am and 11pm. Therefore, we believe that drivers consider a new calendar day as a new progress. However, it is plausible that drivers do not reset their weekly goals every Monday. As a robustness study, we relax the assumptions that the weekly targets are reset every Monday. Instead, drivers might reset the across-day goals only when they start working after being inactive for some time. In this direction, we analyzed the duration of inactivity between any consecutive working days. Among 7,800 drivers who worked at least two days in our dataset, the average number of inactive days between two working days is 2.21. 15% drivers worked everyday on average and 53.30% did not take more than 2 days break. We re-estimated our models by allowing the targets to be reset every time the drivers did not work for at least two days. Allowing the weekly targets to be reset after taking time off from work, our original insights remain qualitatively consistent.

Table C7 Model comparison for shift-level estimation for (i) our main model with both ISF and HSF, (ii) model with ISF only, and (iii) model with HSF only

		Sedan			SUV		
		Full	ISF only	HSF only	Full	ISF only	HSF only
Midday	In-sample AIC	31229	31498	31254	39007	39333	39036
	In-sample BIC	31478	31738	31494	39260	39577	39280
	OOS accuracy	0.929121	0.928407	0.928876	0.900289	0.900189	0.900239
	OOS F1	0.659893	0.655291	0.658388	0.828335	0.828134	0.828249
	OOS log loss	0.206883	0.207941	0.20698	0.269536	0.270614	0.269495
PM peak	In-sample AIC	30399	31566	30405	40349	43982	40486
	In-sample BIC	30649	31807	30646	40603	44227	40731
	OOS accuracy	0.934945	0.934331	0.935029	0.890827	0.88234	0.889837
	OOS F1	0.685106	0.681122	0.685901	0.788181	0.76567	0.785731
	OOS log loss	0.175918	0.181421	0.175939	0.270625	0.284061	0.270518
PM off-peak	In-sample AIC	29807	31915	29988	44928	49398	45481
	In-sample BIC	30059	32157	30231	45182	49642	45726
	OOS accuracy	0.928873	0.926177	0.928661	0.849004	0.844172	0.848733
	OOS F1	0.588916	0.55553	0.586542	0.566988	0.509	0.561383
	OOS log loss	0.17545	0.177709	0.174326	0.310405	0.315422	0.308294
Late night	In-sample AIC	32358	33814	32455	38338	41056	38756
	In-sample BIC	32609	34057	32697	38590	41299	39000
	OOS accuracy	0.919376	0.917993	0.918819	0.859963	0.867975	0.857329
	OOS F1	0.499045	0.466517	0.495284	0.368837	0.305141	0.364001
	OOS log loss	0.195604	0.198253	0.195161	0.290575	0.292882	0.289683

Note: Shaded cell indicates the best-performing model for each vehicle type, shift, and performance metric.

Appendix D: Competition Among Ride-hailing Platforms

In §4.2.4, we discussed four different metrics to control for unobserved demand for ride-hailing services and competition effects. Our main results presented in §5 include all observations from October 2016 to September 2017, the weather information, and the aggregated number of trips on competing platforms ($NumFHV$) as controls for market conditions. For observations between July and September 2017, we conduct an additional analysis to further include $Speed$ and $AggSurge$ as covariates. These new results are qualitatively consistent with our main results. Tables D9 and D10 display the estimates for the first-stage estimation of whether or not to work for each shift. We observe a generally positive income elasticity, income targeting behavior, and inertia throughout all the shifts. Speed appears to have a negative impact on the decision to work in general, suggesting that drivers are less likely to work for the focal platform when there is less traffic. The aggregated surge has also a negative impact on the decision to work. This is to be expected: given that the financial incentive for the focal platform is fixed and known, drivers are less likely to work when the outside option is more appealing.

The results for the second stage are relatively consistent as well (see Tables D11 and D12). Higher hourly earnings appear to be associated with a longer work duration for most shifts. Income targeting behavior becomes less significant. Inertia is stronger earlier on in the day. Finally, we observe that, conditional on driving for the shift, drivers are less influenced by the traffic conditions or by the potential surge pricing from other platforms.

For the day-level analysis, we find that, in the first-stage estimation, positive income elasticity and income targeting behavior became less apparent. Sedan drivers responded positively to the hourly offer from Tuesday to Thursday, whereas SUV drivers did not. The effect of cumulative earnings is generally insignificant, except

Table C8 Model comparison for day-level estimation for (i) our main model with both ISF and HSF, (ii) model with ISF only, and (iii) model with HSF only

		Sedan			SUV		
		Full	ISF only	HSF only	Full	ISF only	HSF only
Tue	Log likelihood	−5208.5626	−5217.8206	−5208.5678	−6505.8704	−6516.3806	−6506.3123
	In-sample AIC	10459	10476	10457	13054	13073	13053
	In-sample BIC	10618	10627	10608	13214	13225	13205
	OOS accuracy	0.873914	0.872975	0.873914	0.760946	0.761228	0.760665
	OOS F1	0.566236	0.566853	0.566236	0.680827	0.682516	0.67997
	OOS log loss	0.327388	0.331084	0.32732	0.520346	0.521589	0.520359
Wed	Log likelihood	−4893.78	−4901.438	−4896.374	−5995.2864	−6004.9009	−6002.0495
	In-sample AIC	9830	9843	9833	12896	12902	12907
	In-sample BIC	9988	9994	9984	13056	13055	13059
	OOS accuracy	0.86754	0.866448	0.867649	0.788416	0.785921	0.789992
	OOS F1	0.581956	0.578512	0.580712	0.721232	0.717895	0.723691
	OOS log loss	0.330561	0.331365	0.330675	0.464833	0.466668	0.464117
Thu	Log likelihood	−4866.1283	−4880.8343	−4866.552	−5621.9006	−5664.6398	−5621.9117
	In-sample AIC	9774	9802	9773	12033	12050	12044
	In-sample BIC	9933	9953	9924	12192	12201	12196
	OOS accuracy	0.880851	0.879905	0.880851	0.799005	0.793461	0.802274
	OOS F1	0.622472	0.622866	0.622754	0.758456	0.754519	0.761038
	OOS log loss	0.304878	0.306166	0.304879	0.453026	0.456261	0.452309
Fri	Log likelihood	−4496.1583	−4508.9092	−4497.1832	−4137.7269	−4149.3907	−4137.7278
	In-sample AIC	9034	9058	9034	11286	11369	11284
	In-sample BIC	9191	9207	9183	11445	11521	11435
	OOS accuracy	0.881711	0.880621	0.88159	0.796355	0.794475	0.7965
	OOS F1	0.615445	0.611746	0.615203	0.742878	0.738739	0.743108
	OOS log loss	0.332035	0.332201	0.332327	0.443663	0.449158	0.443652
Sat	Log likelihood	−3491.9085	−3511.7632	−3492.5465	−4137.7269	−4149.3907	−4137.7278
	In-sample AIC	7026	7064	7025	8317	8339	8315
	In-sample BIC	7178	7208	7170	8470	8484	8460
	OOS accuracy	0.854832	0.85149	0.853897	0.769978	0.768568	0.769821
	OOS F1	0.501835	0.483015	0.498394	0.35614	0.340331	0.356548
	OOS log loss	0.370802	0.372793	0.371027	0.453541	0.457369	0.453933
Sun	Log likelihood	−2871.6076	−2905.6797	−2874.72	−3272.6362	−3324.0522	−3284.8581
	In-sample AIC	5785	5851	5789	6587	6688	6610
	In-sample BIC	5932	5991	5929	6735	6829	6750
	OOS accuracy	0.872415	0.871242	0.872562	0.822791	0.815261	0.818273
	OOS F1	0.459627	0.449184	0.460583	0.336882	0.310861	0.330456
	OOS log loss	0.305811	0.317253	0.308561	0.380171	0.39315	0.386932

Note: Shaded cell indicates the best-performing model for each vehicle type, day, and performance metric.

Table D9 Estimates for the shift-level first-stage estimation for sedan drivers during Summer 2017

Sedan	Offer	ISF	HSF	Speed	AggSurge
Mid-day	0.0075***	-0.0354**	3.6385***	-0.0298	-2.9551***
PM peak	-0.0209***	-0.0016*	0.4743***	-0.0536**	-3.9532***
PM off-peak	0.0136***	-0.0034***	0.413***	0.0132	-1.1326**
Late night	0.01079**	-0.004***	0.38036***	-0.07055***	-0.51665
Note:					*p<0.05; **p<0.01; ***p<0.001

Table D10 Estimates for the shift-level first-stage estimation for SUV drivers during Summer 2017

SUV	Offer	ISF	HSF	Speed	AggSurge
Mid-day	0.0035**	-0.0535***	4.3936***	0.0007	-2.5716***
PM peak	-0.0433***	-0.0024***	0.5249***	-0.0563***	-3.6690***
PM off-peak	0.0028	-0.0024***	0.3414***	-0.0121	-0.2124
Late night	0.0085***	-0.0023***	0.2945***	-0.0785***	0.0920
Note:					*p<0.05; **p<0.01; ***p<0.001

Table D11 **Estimates for the shift-level second-stage estimation for sedan drivers during Summer 2017**

Sedan	Earnings	ISF	HSF	Speed	AggSurge	IMR
Mid-day	0.008	-0.019***	1.604***	-0.039	0.0003	***
PM peak	0.025*	-0.001	0.084***	0.012	0.029	***
PM off-peak	0.003	-0.003***	0.006	-0.0001	0.147	***
Late night	0.03***	0.001	-0.071**	0.019	0.11*	***
Note:	*p<0.05; **p<0.01; ***p<0.001					

Table D12 **Estimates for the shift-level second-stage estimation for SUV drivers during Summer 2017**

SUV	Earnings	ISF	HSF	Speed	AggSurge	IMR
Mid-day	-0.001	-0.008	1.819***	-0.034	-1.008	***
PM peak	0.062***	-0.0002	0.245***	-0.053***	-0.421	***
PM off-peak	0.004***	-0.0002*	0.033***	-0.002	-0.027	***
Late night	0.022***	0.0001	0.021	-0.006	0.843	
Note:	*p<0.05; **p<0.01; ***p<0.001					

a sign of income targeting at the end of the week. However, inertia is still significant and apparent for most days, Thursday through Sunday for sedan driver, and Wednesday through Sunday for SUV drivers.

Lastly, for the second-stage estimation, we find no significant estimates for our key variables. This is in line with our original results, which led us to conclude that the decision on the work duration for the day was not determined at the beginning of the day.

Appendix E: Potential Mechanisms for Behavioral Effects

We conduct additional analyses to identify potential underlying mechanisms that drive income targeting and inertia. First, we test whether experience on the platform moderates inertia as well as labor supply elasticity and income targeting. We replicate some of the findings from Sheldon (2016) on whether experience affects labor supply elasticity. Since our data spans one full year (October 2016–September 2017), and there is no information on the date at which each driver joined the platform, we only consider drivers who joined the platform for the first time within our data (e.g., started after October 10, 2016 but before September 30, 2017) for this analysis. We then measure the experience of each remaining driver by splitting the observations into bins of working days in increments of ten, that is, the first ten days that the driver works for the platform correspond to the first bin, days eleven to twenty correspond to the next bin, and so forth until the last bin which consists of days 260 to 270. Overall, there are 27 different bins. These bins of experience levels are included as dummy variables as well as the interaction term with the instrument, capturing the marginal effect on the elasticity.

Following the specification used in Sheldon (2016), we find that the income elasticities are positive and do not appear to be affected by experience (see Table E13 (i) below). However, when including the other key variables, ISF and HSF, we infer the impact of experience as follows. For the income elasticities, controlling for ISF and HSF, we observe a positive but noisy trend in the impact of experience. Notably, elasticities after 100 days of work are higher than those of early work days. The negative impact of ISF and the positive impact of HSF are significant and with a larger magnitude for the first 80 days of work compared to later. This suggests that drivers with more experience working on the focal platform exhibit less income targeting and inertia relative to the drivers who just started out, similar to the findings in Sheldon (2016).

Table E13 (ii) illustrates this result for the first 150 working days. Therefore, inertia could reflect learning on the platform: the longer a driver has worked recently means that s/he has gained more information that motivates her/him to work more later on. Such learning of new information becomes less important as the driver has gained more experience working on the platform.

Table E13 Elasticities over work experience.

	(i) Replicating Sheldon (2016)	(ii) Our model		
Working days	Hourly earnings	Hourly earnings	*ISF*	*HSF*
1-10	0.387***	0.521***	-0.0002***	0.012***
11-20	0.372***	0.499***	-0.0003***	0.014***
21-30	0.372***	0.494***	-0.0003***	0.016***
31-40	0.370***	0.492***	-0.0001	0.011***
41-50	0.373***	0.496***	-0.0002**	0.014***
51-60	0.377***	0.504***	-0.0002*	0.013***
61-70	0.357***	0.484***	-0.0002*	0.013 ***
71-80	0.363***	0.493***	-0.0002	0.010*
81-90	0.356***	0.491***	-0.00002	0.004
91-100	0.372***	0.509***	-0.0002	0.009
101-110	0.381***	0.531***	-0.0002	0.009
111-120	0.377***	0.525***	-0.0003+	0.011+
121-130	0.384***	0.532***	-0.0002	0.007
131-140	0.381***	0.535***	-0.0003+	0.010
141-150	0.383***	0.528***	-0.0004*	0.015*

Note: +p<0.1; *p<0.05; **p<0.01; ***p<0.001

Finally, we identify potential associations between long daily work hours that could have been triggered by inertia and driver experience as well as market conditions. Specifically, we regress the daily work hours on these factors for driver-dates where we observe inertia and control for driver and time fixed effects. As illustrated in Table E14, we find that inertia is more prevalent among drivers with less experience on the focal platform, or on days when the financial offers on the focal platform have a low mean but a high variance across shifts, or when the average competition intensity is high but the variance is low. While these findings only provide correlational evidence, we believe that they are useful in guiding future researchers to further investigate mechanisms underlying inertia.

Appendix F: Psychological Explanations for Our Main Results

Our main results suggest that workers on our focal platform exhibit different behaviors regarding cumulative earnings and recent work duration. We believe such different behaviors stem from the fact that people perceive the value of time and money differently. Contrary to a common saying that time is money, empirical research from psychology shows that decisions about time follow different rules than decisions about money. For example, Leclerc et al. (1995) finds that people are more averse to uncertainty with time as contrasted with money. In other words, people are risk averse with respect to decisions in the domain of time loss despite being risk-seeking with respect to decisions involving monetary loss. The authors concluded that because time is less substitutable than money, being certain is more important for decisions about time, and people are more averse when there is uncertainty about the allocation of time. Soman (2001) shows that people

Table E14 Drivers of long daily work hours when inertia was observed.

	(i)	(ii)
Experience (weeks)	-0.067^{***} (0.006)	-0.005^{***} (0.001)
Mean offer across shifts	-0.075^{***} (0.002)	-0.054^{***} (0.002)
SD offer across shifts	0.036^{***} (0.003)	0.016^{***} (0.003)
Mean competing volume	0.0001^{***} (0.00000)	0.00004^{***} (0.00000)
SD competing volume	-0.00005^{***} (0.00000)	-0.0001^{***} (0.00000)
Driver FE	Yes	Yes
Day of Week FE	Yes	No
Date FE	No	Yes
Weather	Yes	Yes
Observations	233,789	233,789
R^2	0.021	0.011

Note: $^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

do not mentally account for their time in the same way as they account for money as the former is more difficult, while Okada and Hoch (2004) demonstrates that people spend time in a systematically different way from spending money because the value of time is of greater ambiguity. The distinction of attitude toward time and money applies to work motivation and decisions as well. Workers who can adjust their own work schedules are found to be influenced by internal reference targets. Depending on the context, workers may form only a target for income (Camerer et al. 1997), a target for time (Farber 2015), both in the same direction (Crawford and Meng 2011), or both in the opposite direction as observed in our work. DeVoe and Pfeffer (2007) shows that organizational practices such as how firms pay their employees may influence employees' psychological evaluation of time and the tradeoffs they make between time and money.

Our key insight suggests that gig economy workers may exhibit inertia at work. In our context, inertia refers to the positive correlation between the recent work duration and the decision to start a new work shift. We have identified the following three potential explanations of inertia from the fields of psychology, organizational behavior, and management.

(i) First, inertia could be linked to the concept of experience of flow from positive psychology. A flow state is the mental state in which a person performing an activity is fully immersed in a feeling of energized focus, full involvement, and enjoyment in the process of the activity (Csikszentmihalyi and Csikszentmihalyi 1992). The complete absorption into the activity affects how the person perceives the sense of time, leading to a continuation of performing the task even though the marginal benefit is negligible. Flow theory postulates key conditions required to achieve a flow state. These conditions include clear goals and task structure, clear and immediate performance feedback, a balance between the challenges of the task and one's own skills, one's feeling of control, and one's intrinsic motivation. Gig economy workers are likely to meet these conditions since gig tasks typically have a known set of goals and structure, feedback (e.g., from customers) and compensation are provided frequently, and workers are generally skilled at the particular tasks and have some control over their decisions (e.g., work schedule). Csikszentmihalyi and LeFevre (1989) suggests that flow can be experienced in both work and leisure settings, but more dominantly in the former. Among different leisure activities, the authors find that driving is the most common task that generates the flow experience. This finding fits well with our analysis of ride-hailing drivers. Therefore, it is possible that drivers on our platform are more likely to work if they recently worked for a longer duration because they are more likely to experience the flow state.

(ii) Second, inertia may reflect work addiction caused by stochastic rewards. Applying insights from neuroscience research that stochastic rewards could act as a motivator, Corgnet et al. (2020) conducts a series of behavioral experiments to investigate the relationship between stochastic rewards and workers' likelihood to quit working on effortful tasks. The authors found that participants who were offered a stochastic rate of compensation stayed working for a longer period than those offered a deterministic rate. The persistence on the tasks is linked to stress generated by the uncertainty. In a gig economy setting, compensation to workers is typically determined in response to real-time market conditions (e.g., demand) and depends on the specific task and workers' performance. Work addiction among gig workers has been documented and attributed to the rate of compensation (Kruzman 2017). For our focal platform, financial incentives are decided and communicated to drivers ahead of time, but drivers' opportunity costs (e.g., incentives from competing platforms) are not deterministic. Therefore, it is possible that inertia is related to workaholism driven by uncertain rewards.

(iii) Third, inertia, as the absence of fatigue, could be associated with gig workers' flexibility in deciding work schedule. Watanabe and Yamauchi (2016) shows that when workers voluntarily opted to work for a longer period, there is a positive effect on their work-life balance due to the enjoyment of the work itself or increased rewards. Having control over work duration and being compensated for the work are found to be important for workers' satisfaction. Similarly, workers who voluntarily chose to work overtime did not feel more fatigued but instead felt satisfied as long as they chose their own schedule (Beckers et al. 2008). Although the concept of overtime work can only be applied loosely to gig workers since they have full control of their entire schedule, these findings highlight the potential beneficial impact of the flexibility to choose one's own work schedule: reduced fatigued and increased satisfaction. A study on technical contractors whose schedule were not decided by the organization shows that, despite having full control over their work schedule and perceiving the privileged flexibility, these contractors chose to work long hours and appeared to follow a less flexible schedule (Evans et al. 2004). They considered leisure time as a period of loss without pay and hence they sought to minimize time away from work. Using the British Household Panel Survey, DeVoe et al. (2010) observes that individuals who received hourly wage are more willing to trade their leisure time to work and earn more money than those receiving a salary pay. Putting these findings together, we conclude that in our setting where workers can freely choose their own work schedule and receive a hourly pay, they are more likely to work for longer, become more satisfied with long work hours, and feel less fatigue.

Appendix G: Policy Analysis: NYC's Driver Income Rules

Here, we take the perspective of a policymaker and leverage our insights to evaluate the impact of regulations on the welfare of gig workers. In December 2018, the TLC passed *Driver Income Rules* to protect driver earnings, requiring ride-hailing platforms to compensate drivers by a minimum amount for each trip at the rate equivalent to \$27.86 per hour. Since there were no such rules during the timeframe of our data, we can only perform a counterfactual analysis to quantify the impact of this new regulation on the workers' welfare, particularly on their earnings.

We compare three different policies. First, our *optimal* policy is the targeted incentive allocation policy introduced in §6.1, which optimizes incentives based on drivers' predicted probability to work. Second, a *minimum wage* policy adds a constraint to the optimal policy such that every driver must be guaranteed a minimum hourly offer of $27.86. Finally, we use the observed incentives in the data as a benchmark or *current* practice. Outcomes of interest are the average hourly offer across all drivers and the average hourly earnings across drivers who are predicted to work. The counterfactuals are performed using the data between January and September 2017 in the same fashion as in §6.1.

We find that the minimum wage policy slightly increases the average hourly offer among drivers compared to the optimal policy and to current practice, but the differences are not statistically significant. However, these policies lead to significantly different average hourly earnings among drivers predicted to work. Conditional on drivers who worked, our analysis suggests that, compared to the current practice, the minimum wage policy significantly improves the average hourly earnings. However, drivers could have earned 10 to 23% more per hour if the incentives were optimally allocated by following the optimal policy without the minimum wage constraint.

The minimum wage policy appears to be beneficial to the workers compared to the platform's current practice. However, as firms are becoming more data-driven and potentially adopting more sophisticated incentive policies (such as our proposed optimal policy), the current minimum wage rule may no longer improve the welfare of the workers. In this case, if the focal platform implements the optimal policy, the regulation decreases workers' pay on average. This also highlights the importance of understanding how gig workers make decisions. The TLC does have detailed information regarding trips operated by ride-hailing drivers but may not have access to how platforms allocate incentives or how drivers decide their flexible schedules. Without such knowledge, policymakers are prone to regulations that could be suboptimal.