The Earnings Penalty of Rest: The Effect of Slacking on Taxi Drivers' Fare Earned

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Abstract:

Quiet quitting -- doing the bare minimum at one's job -- has risen significantly in popularity after the COVID-19 pandemic produced systematic changes in the working habits of the global labour force. In this paper, we are analyzing the effect of slack time on taxi drivers' earnings, as they would directly reflect the workers' productivity. Using the data set on New York City taxi drivers' shifts in 2009, we found a significant negative relationship between average hourly slack time and average hourly fare earned in a driver's shift. After controlling for driver experience level, driving conditions, and shift characteristics, the effect becomes more economically significant. The differential effect of slack time on earnings between new and experienced drivers is statistically significant and positive, indicating that slacking has a higher effect on performance for less experienced workers.

1. Introduction

The COVID-19 pandemic has caused prolonged social isolation and worldwide economic uncertainty, which have systematically reduced employee engagement and exacerbated stress. In the aftermath, quiet quitting, or the idea of doing the bare minimum at one's job, had become a prevalent trend (Masterson 2022). If left unchecked, the systematic decline in worker productivity could have a significant impact on the global economy. This phenomenon can be observed through the general decline in the total hours worked in the U.S. after the pandemic had subsided (Lee, Park, and Shin 2023, 1). In 2022, U.S. labour productivity in non-farm businesses declined by an unprecedented 1.7% on average, the lowest since 1974 (U.S. Bureau of Labor Statistics 2023).

The taxi market serves as a uniquely useful environment to analyze the effect of slacking on worker productivity, as the drivers have substantial control over how they find customers, and their performance is directly reflected in their earnings (Haggag et al. 2017, 71). There is little existing literature that analyzes the effects of quiet quitting, or slacking, on taxi drivers' fare earned, as the widespread phenomenon occurred relatively recently. Related literature focused on analyzing worker motivation, and the researchers found that incentive contracts have a positive impact on worker productivity and earnings (Heywood, Jirjahn, & Struewing 2021). We aim to fill in the gap by analyzing the effect of slacking on employee performance, which can be more directly translated to the macroeconomic impact of quiet quitting.

In our research, we expand upon the study done by Haggag et al. (2017), which found that neighbourhood-specific experience has a positive effect on driver earnings for licensed New York City (NYC) taxi drivers in 2009. In addition to analyzing the effect of slacking on the drivers' fare earned, we also intend to examine how experience level influences the variables' relationship.

2. The Context and Data

We begin our analysis by obtaining data from Haggag et al.'s paper in 2017. The authors manipulated public data from the Taxi & Limousine Commission database and the 2009 NYC Census Tract. Our observational data is cross-sectional and contains 1,052,939 observations. Each observation represents a shift conducted by a licensed NYC yellow taxi driver in the 2009 calendar year. In total, 6,293 drivers' shift data were collected, including those with destinations outside of NYC's five boroughs.

For the analysis, our population of interest encompasses the shifts conducted by NYC taxi drivers in 2009. Our main variable of interest is the average hourly slack time (including search, wait, and break time) in a driver's shift in minutes, which we created in Stata by dividing the total slack time by the total hours in a driver's shift. Our outcome variable is a 2009 NYC driver's average hourly fare earned in USD. As seen in Table 1, the average hourly slack time ranges from 0 to 60 minutes, and the drivers' average hourly fare ranges from $0 to $258.33. Furthermore, we analyzed the distributions of our variables. As seen in Figure 1, our main variable of interest is approximately normally distributed and shows that the mean of the average slack time per hour taken by drivers is 29.37 minutes. It is surprising that on average, the total gaps in between rides accounts for almost 50% of the shift. As shown in Figure 2, the distribution of the outcome variable is extremely positively skewed and exhibits that the average hourly fare earned by 2009 NYC drivers is $25.86. Additionally, in order to ensure data consistency and sufficient variation within the observations, we excluded the data points with exactly 60 minutes of average hourly slack time, as those would correspond to drivers that are not working.

3. Regression analysis

3.1 Simple Linear Regression

Our baseline model focuses on the relationship between average hourly fare earned by a 2009 NYC driver and the average hourly slack time spent searching, waiting for customers, and taking breaks. Therefore, we estimate their relationship via the following equation:

$$\textbf{avg\_earn} = \boldsymbol{\beta 0} + \boldsymbol{\beta 1} * \textbf{avg\_slacktime} + \boldsymbol{\varepsilon}$$

such that the dependent variable (avg_earn) is the average hourly fare earned, and the independent variable (avg_slacktime) measures the minutes of average hourly gap taken between rides in a shift, including search, wait, and break time. We utilized robust standard errors to eliminate heteroscedasticity.

As seen in model (1) from Table 2, our simple regression found that a 2009 NYC driver taking ten minutes more slack time per hour is correlated with $5.52 USD less average hourly total fare earned, along with an exceedingly low standard error of 0.0008. With a 95% confidence interval, we expect that the average decrease in total fare earned associated with ten more minutes of average hourly slack time is between $5.51 and $5.54. The result is highly statistically significant, as the t-statistic is very large at –661.77. We reject the null hypothesis $\beta 1 = 0$ at 1% significance level, indicating that there is an underlying relationship between the drivers' average hourly slack time and their average hourly fare earned. The estimated slope coefficient is relatively small but economically significant. For instance, the change of one standard deviation in slack time is associated with 71% of a standard deviation change in shift fare. In other words, a sizable difference in average hourly slack time is associated with a relatively large difference in predicted average hourly fare in a shift.

There is concern that the simple model violates Least Squares Assumption (LSA) 1, which states that $E(u \mid x) = 0$. The regression fails to control for other factors that can affect the drivers' average hourly earnings in a shift and that are also correlated with average hourly slack time, including driver's characteristics, shift characteristics, and driving conditions. Thus, we will include other explanatory variables that can control for those factors, such as accumulated experience, speed per ride, and the easiness of searching for a customer based on the time and location.

Additionally, we also violate LSA 2, which states that the sample is independently and identically distributed. Firstly, distribution independence requires that there is no correlation among our observations. However, some of the shifts are conducted by the same driver, as indicated by them being associated with identical driver IDs, so the data inevitably contains shifts that are correlated with each other due to the drivers having recurring working habits. Furthermore, the requirement of having identical distributions implies that every observation has the same probability distribution. However, since the TLC trip record data is collected by technology providers, only the taxis that are equipped with the appropriate technology are being observed, which results in non-random sampling in our data (NYC Taxi & Limousine Commission 2023).

3.2 Multiple linear regression

To further analyze the effect of average hourly slack time on average hourly fare earned, models (2) through (4) run a series of multiple linear regression to control for previously omitted variables.

We set our equation as follows:

$$avg\_earn = \beta 0 + \beta 1 * avg\_slacktime + \beta 2 * end\_fn60\_puma\_mean + \beta 3 * shift\_miles\_perride + \beta 4 * shift\_speed\_perride + \beta 5 * log\_all\_exper + \varepsilon$$

In model (2), we control for the driving conditions, which is determined by the easiness of finding customers based on the drivers' timing and location. The easiness variable is measured based on which Public Use Microdata Area (PUMA), day of the week, and time of the day the shift took place. New York City is divided into 55 PUMAs, with each area approximately corresponding to a Community District (e.g. Upper East Side) (U.S. Census Bureau, 2010). The circumstances with higher chances of traffic congestion and accidents, or those with the lowest average fares, were assigned a lower value (Haggag et al. 2017, 78). Because easier situations (drivers located in a busy area during rush hour on the weekends) tend to enable drivers to have less slack time and higher earnings, not controlling for this variable would cause β1 to be negatively biased, or in other words, overstate the negative effect of slack time has on hourly earnings. In this specification, we found that a 2009 NYC taxi driver slacking ten minutes more per hour is associated with a $5.40 decrease in average hourly fare earned at 1% significance level. As predicted, keeping the easiness variable constant corrected β1's negative bias. However, it is important to note that the number of observations decreased, as the easiness variable was only calculated for 1,038,761 shifts, but our result is still highly statistically significant. Additionally, we believe that the easiness variable would serve as a control variable for the proportion of average hourly slack time that the drivers spent searching and waiting for customers. As the easiness variable is negatively correlated with the amount of time the drivers would need to search for the next customer, controlling for the easiness of the driving conditions further isolates slack time as a measurement of the drivers' idleness, and it further concentrates our analysis towards identifying the true effect that quiet quitting has on the drivers' average hourly earnings.

In model (3), we improve upon our model by controlling for ride characteristics, such as the speed and miles driven per ride in a driver's shift. Faster and longer rides both correlate to higher fare and longer slack time, and controlling for those variables would eliminate β1's positive bias. This finding is intuitive as the standard metered fare increases by 70 cents for every 1/5 mile (0.32 km) when the taxi is traveling above 12 miles per hour (NYC Taxi & Limousine Commission, 2023).

As predicted, the new model shows that ten more minutes of average hourly slack time corresponds to a larger \$6.05 decrease in average hourly fares earned at 1% significance level.

In model (4), we further control for driver characteristics by including the log of drivers' accumulated experience. The authors constructed the experience variable with the cumulative number of shifts that a driver conducted on a particular day, and it measures the drivers' experience level across all time and space conditions (Haggag et al. 2017, 84). Our prediction is that more experienced drivers may take shorter breaks and earn higher fares, and controlling for driver experience would correct $\beta 1$'s negative bias. After controlling for all aforementioned variables, we determined that a 2009 NYC taxi driver having ten more minutes in average hourly slack time is associated with a \$6.01 decrease in average hourly fare earned in a shift. By including the variables in driving conditions, driver characteristics, and ride characteristics in our regression, we now have a more precise understanding how idleness affects the average hourly earnings of a 2009 NYC taxi driver.

However, we still violate LSA 2, since we cannot eliminate the occurrence of multiple observations originating from the same drivers due to technical limitations in Stata BE[1]. In regard to our finding, it is evident that the effect of idleness generally becomes more economically significant as we control for more characteristics in our model. Additionally, we created a correlation matrix to examine if we follow the LSA 4 assumption of no multicollinearity. As seen in Table 3, all the variables have weak correlations, with the highest correlation value being less than 0.5, which signals that we did not violate LSA 4. Furthermore, to expand upon our results, we want to examine the effect laziness has on the average earning if we divide the drivers into two groups based on their experience levels.

4. Extension: Effect of Average Hourly Slack Time on Average Hourly Fare Earned for New and Experienced Drivers

To further analyze the effect of driver experience on our results, we generated a new interaction term to analyze the systematically different effects of average hourly slack time on average hourly

[1] As we had too many data points, Stata BE did not have the capacity to generate dummy variables for each driver so that we could control for driver fixed effects in our regression.

earnings between new and experienced drivers. The authors created the dummy variable new_driver, which is equal to 1 for the drivers whose first shifts started on or after April 1st, 2009, and conducted at least 50 shifts between their entry date and December 31st, 2009 (Haggag et al. 2017, 75). By multiplying new_driver with avg_slacktime, we were able to generate the interaction term new_slacktime. Our equation in model (5) is as follows:

avg_earn = β0 + β1 * avg_slacktime + β2 * end_fn60_puma_mean + β3 * shift_miles_perride + β4 * shift_speed_perride + β6 * new_driver + β7 * new_slacktime + ε

The differential effect of ten more minutes of average hourly slack time on average hourly fare is \$0.06 with a low standard error of 0.002 and a t-statistic of –2.93, so we reject the null hypothesis β7 = 0. We left out the variable log_all_exper, as we are solely analyzing the effect of experience through the interaction term. Our result indicates that the effect of average hourly slack time on average hourly earnings is statistically significantly higher for new drivers than for experienced drivers. The differential effect is small in magnitude and not economically significant.

5. Limitations of Results

The limitations of our results' internal validity lie in the following aspects: 1) omitted variable bias, 2) selection bias, 3) reverse causality, and 4) potentially wrong functional formlimitations of linear regression model. Firstly, there are other uncontrolled driver characteristics that affect fare earnings and correlate with slack time, such as age and total household income. Even though the magnitude of our R-squared in all models indicates that more than 50% of the variation in average hourly earnings is explained by the variations in our chosen explanatory variables, not controlling for those omitted factors would deviate our results from the true relationship between average hourly slack time and fare earned.

The violation of LSA 2 also skews our results, as there are multiple data points originating from the same driver, which causes dependence in our observations. Furthermore, there is concern that our data suffer from simultaneous causality bias, as it is intuitive that drivers with higher average hourly earnings would take longer breaks. Additionally, there is restriction to the linear regression model. The model does not adjust to the data responsively and , which leads to high bias, that which is defined as the error between the expected model's prediction and the actual observation.

Thus, the model can be underfitting. To mitigate such the limitations of the underfitting model, we can introduce a more flexible model that adjust to the data more responsively to reduce the error.

There are also concerns regarding our results' external validity. Since the data is only collected in New York City, we are restricted to only being able to make an inference of the population of all taxi drivers in New York. Moreover, the data is only limited to the 2009 calendar year, so our results may not be applicable to more recent years due to possible undetected temporal effects.

6. Conclusion

This paper investigates the effect of the amount of time that a 2009 NYC taxi driver slacks off during their shifts on their average hourly fare earned. We refer to the research done by Haggag et al. (2017) and conclude that there is a strong negative relationship between average hourly slack time and average hourly earnings. The effect becomes more economically significant after controlling for factors that are both correlated with slacking and earnings, such driving condition as measured by the easiness to earn fare based on timing and location, driver characteristics as measured by the drivers' experience level, and shift characteristics as measured by the speed and miles driven per ride in a driver's shift.

We also examine the distributions of our outcome variable "average hourly fare earnings in shift" and treatment variable "average hourly slack time in a shift". Even though we have an extremely large sample size, we still examine the effect of outliers on the deviation of our normality assumption and ensure that they had minimal effects on our regression result.

LastlyAdditionally, we find found a small but statistically significant differential effect of average hourly slack time on earnings between experienced and new taxi driver groups. Based on the adjusted R-squared, we conclude that our multiple linear regression has a satisfactory fit of the data, as more than 60% of the variation in average hourly fare earned is explained by the variation in our chosen treatment variables.

There are still limitations in our paper due to several threats to the internal validity from omitted variable bias, selection bias, reverse causality, and limited fitting in the functional form. As the paper’s sample selection is limited in both time period and location, we would not assume external validity or apply our results to more recent years or in locales other than New York City. Nevertheless, our finding provides fresh insights to the effect of quiet quitting, or slacking, in taxi drivers’ earnings, and they could influence future policies in other manual labour industries.

7. Reference

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8. Appendix

Figure 1: Box Plot and Histogram of the average hourly slacktime in shift

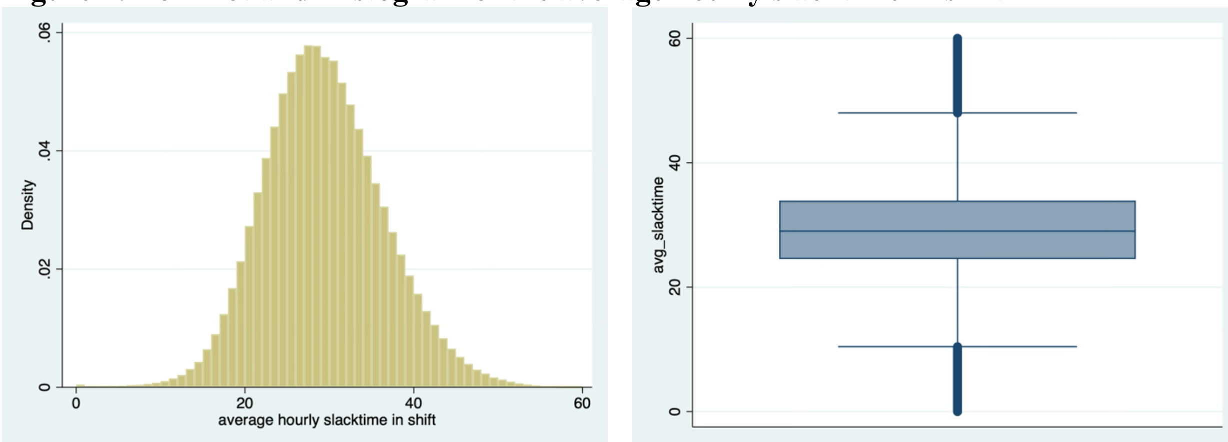

Figure 2: Box Plot and Histogram of the average hourly earnings in shift

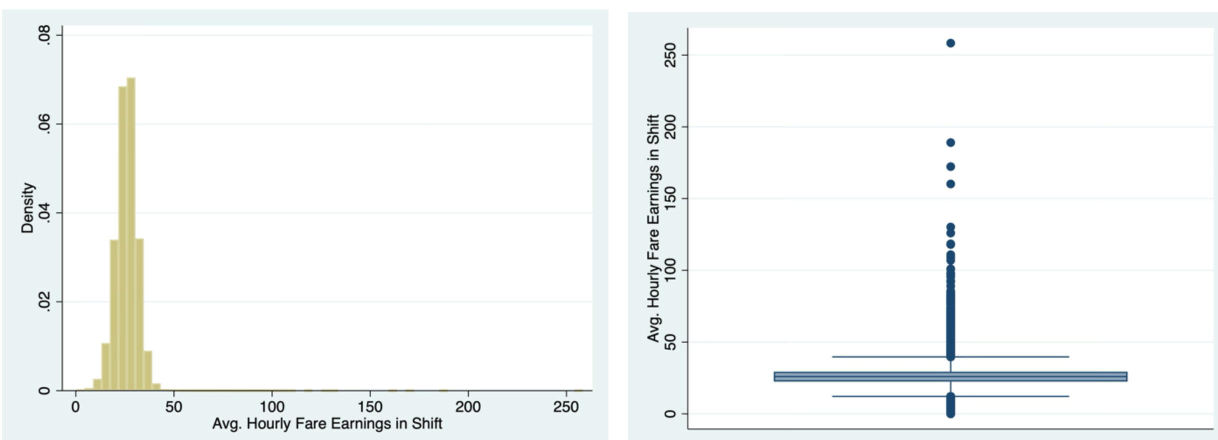

Table 1

Descriptive Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
avg earn	1052939	25.864	5.516	0	258.334	11.982	38.793	.179	9.766
avg slacktime	1052938	29.369	7.137	0	60	13.626	47.397	.197	3.372
end fn60 puma mean	1038762	26.766	3.731	2.5	139.37	18.272	33.934	-.135	4.079
shift miles perride	1052939	3.051	1.718	0	48.18	1.344	10.713	3.816	26.792
shift speed perride	1052929	14.063	6.163	0	4231.385	7.118	27.378	337.444	217000
log all exper	1050604	7.903	.835	.693	9.402	4.812	9.027	-2.558	16.081

Note. Unit of observation is a shift conducted by a New York City taxi driver in 2009. The data contains shifts from 6,293 drivers. In the table, end fn60 puma mean is the variable that measures the fare conditions in a shift. Depending on which Public Use Microdata Area (PUMA), day of the week, and time of day the shift took place, the conditions with higher chances of traffic congestion and accidents, or those with the lowest average fares, were assigned a lower value. Additionally, log all exper refers to the log of the drivers' accumulated experience, which is constructed with the cumulative number of shifts that a driver conducted on a particular day. The variable measures their experience level across all time and space conditions.

Table 2: Multiple Regression of avg_slacktime on avg_earnings and other tract characteristics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	model 1	model 2	model 3	model 4	model 5
avg_slacktime	-0.552***	-0.540***	-0.605***	-0.601***	-0.604***
	(0.001)	(0.001)	(0.024)	(0.024)	(0.023)
end_fn60_puma_mean		0.167***	0.160***	0.158***	0.160***
		(0.001)	(0.010)	(0.009)	(0.010)
shift_miles_perride			0.255	0.271	0.254
			(0.225)	(0.225)	(0.225)
shift_speed_perride			0.213	0.211	0.213
			(0.138)	(0.136)	(0.138)
new_driver					0.104
					(0.074)
new_slacktime					-0.006***
					(0.002)
log_all_exper				0.307***	
				(0.041)	
Constant	42.090***	37.234***	35.567***	33.096***	35.566***
	(0.025)	(0.042)	(0.300)	(0.063)	(0.312)
Observations	1,052,928	1,038,760	1,038,760	1,038,760	1,038,760
R-squared	0.511	0.531	0.603	0.605	0.603

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model (1):
Simple Linear regression

avg_earn	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
avg_slacktime	-.553	.001	-685.58	0	-.554	-.551	***
Constant	42.075	.025	1708.31	0	42.026	42.123	***

Mean dependent var	25.842	SD dependent var	5.438
R-squared	0.526	Number of obs	1052243
F-test	470020.248	Prob > F	0.000
Akaike crit. (AIC)	5765034.834	Bayesian crit. (BIC)	5765058.567

**** p<.01, ** p<.05, * p<.1*

Model (4):
Multiple Linear regression

avg_earn	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
avg_slacktime	-.601	.024	-25.50	0	-.647	-.555	***
end_fn60_puma_mean	.159	.009	17.13	0	.141	.177	***
shift_miles_perride	.267	.222	1.20	.23	-.169	.703	
shift_speed_perride	.209	.135	1.54	.123	-.056	.474	
log_all_exper	.311	.04	7.72	0	.232	.389	***
Constant	33.052	.062	534.65	0	32.931	33.173	***

Mean dependent var	25.860	SD dependent var	5.408
R-squared	0.619	Number of obs	1038133
F-test	145764.726	Prob > F	0.000
Akaike crit. (AIC)	5448005.459	Bayesian crit. (BIC)	5448076.576

**** p<.01, ** p<.05, * p<.1*

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3
Correlation Matrix of independent variables

Variables	(1)	(2)	(3)	(4)	(5)
(1) avg_slacktime	1.000				
(2) end_fn60_puma_~n	-0.183	1.000			
(3) shift_miles_pe~e	0.204	-0.069	1.000		
(4) shift_speed_pe~e	0.288	-0.023	0.485	1.000	
(5) log_all_exper	-0.107	0.063	-0.097	-0.022	1.000