MAKING LEMONADE FROM LEMONS: TAXI DRIVERS' RESPONSE TO CANCELLATIONS AND NO-SHOWS

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Abstract—Kőszegi and Rabin (2006) show that workers with endogenous income targets respond differently to anticipated changes and unanticipated shocks in their earnings, and only the latter generates behaviors that contradict the neoclassical model of labor supply. In this paper, we study the impact of booking cancellations and passenger no-shows—a source of unanticipated negative income shocks—on Singaporean taxi drivers' labor supply and productivity. We find that drivers work longer and earn more per hour following cancellations or no-shows, and the effects are strongest when cumulative income is close to the average shift income and become insignificant when the income is too low or too high. This provides compelling evidence for income targeting labor supply, even in the presence of endogenous reference point. In addition, we find that drivers respond more strongly to more recent cancellations and no-shows, suggesting a dynamic nature of the reference point. Moreover, working longer and increasing productivity are substitutable rather than complementary devices, and are chosen by taxi drivers in their own favor: More experienced drivers tend to increase productivity, and solo drivers tend to work more hours.

JEL Codes: J22, J24, D91

I. Introduction

Despite being a building block for many economic models and playing an imperative role in the design of numerous public policies and industrial practices, labor supply is still a controversial topic in economics. The two competing theories are the neoclassical labor supply model, which predicts temporal substitution of leisure for labor when wage rises, and the income target model, which predicts that workers have a target level of income, which, together with loss aversion, motivates them to work harder when wage is low. Empirical studies have shown mixed results not only in different settings, but sometimes even in the same setting using different methodologies. A prominent example is the taxi industry, in which seminal work by Camerer et al. (1997) and later papers, such as Crawford and Meng (2011), Martin (2017), and Thakral and Tô (2018), find evidence for drivers' daily income target. Other studies, such as Farber (2005, 2015), find stronger support for the neoclassical model.

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To reconcile these mixed results, Kőszegi and Rabin (2006) propose a model of reference-dependent preference that formalizes the notion of income targeting while allowing for neoclassical behaviors to exist under certain circumstances. The model's key insight is that sophisticated workers can form their target rationally; for them, reference dependence only matters if the variation in wages is *unanticipated*, because they will adjust their target in response to anticipated changes in a manner that is consistent with the neoclassical model.

Empirical studies of daily labor supply have largely overlooked this distinction between anticipated changes and unanticipated shocks[1]. A common test of reference-dependent labor supply is to show a relationship between intra-day income—either in the form of cumulative earnings up to a point in time, or total earnings during a specific time interval of the day—and subsequent labor supply decisions. However, an insignificant result of this test does not entirely reject reference dependence; it may simply reflect the low level of unanticipated shocks experienced by workers within that specific time and context, or an anticipation formation process that is extremely adaptive to new shocks. For instance, Farber (2015) finds a marginal effect of income on stopping decisions in day shifts, but positive wage elasticity due to negligible variation in transitory unanticipated hourly wage changes among New Year City (NYC) taxi drivers. Thakral and Tô (2018) point out that if the reference point adjusts to recent earnings at a sufficiently fast speed, a reference-dependent worker may act in a manner similar to a neoclassical worker. Several papers use structural models to explicitly account for a worker's anticipation, but this approach requires strong assumptions about how the reference point is formed—and since the reference point is unobserved, these assumptions are difficult to test. As a result, using variation in realized daily earnings constitutes, at best, only a weak test for reference dependence, and at worst, can be misleading about the nature of the labor supply response.

We propose the use of an alternative approach, by exploiting *unanticipated* sources of external income shocks that workers encounter repeatedly over time and examining how these shocks affect workers' subsequent labor decisions. We focus on Singapore's taxi industry, and the income shocks we use are booking cancellations and passenger no-shows—i.e., in which a passenger makes a booking but fails to follow through with the trip, resulting in the loss of time, mileage, and potential earnings for the driver. Passengers' decisions to cancel a booking or not show up are made with little interaction with the driver, and hence are unlikely to be predicted by drivers and factored into their daily income target prior to the booking. Since the subsequent wage rate is not affected by these idiosyncratic events, the neoclassical model would predict no relationship between cancellations and no-shows (C&NS hereafter) and the subsequent supply of labor. In contrast, under

[1] Only a few papers explicitly consider this distinction: Agarwal et al. (2017) investigate the effects of a large anticipated one-time income shock due to a pension withdrawal at age 55, while Andersen et al. (2014) conduct field experiments introducing expected and unexpected earnings shocks to vendors in an Indian open air market.

reference-dependent preference, we would expect drivers to work harder because after C&NS, their realized earnings will fall below the typical level they can achieve with the same amount of worked hours but without C&NS. Essentially, we single out a source of income shocks that is reliably unanticipated, which enables us to construct a transparent test for reference-dependent preference and a straightforward interpretation of the results.

This paper also addresses a growing question in the reference dependence literature: How is the reference point determined? If the reference point is fixed, wage elasticity of the labor supply will be close to -1 and there will be little variation in daily income—an outcome that is easily rejected in most contexts that involve flexible-hour workers. To explain the high variation in daily income among these workers, some form of the reference point's ability to adapt to market conditions must be present. In the context of the NYC taxi industry, Thakral and Tô (2018) show that the reference point can even respond to within-day earning variation, and more recent earnings have a greater effect on labor supply than earlier earnings. Our approach of using unanticipated income shocks complements this line of research. C&NS, our source of income variation, are random events that can occur anytime during the day, and their timing can be used to test the dynamic nature of the reference point. A recent C&NS and a C&NS that occurred early in the shift, given similar characteristics, cost drivers the same amount of potential earnings—and hence, under a static reference point, would have the same effect on subsequent labor decisions. On the other hand, if drivers continually adjust the reference point when new shocks come in, we would expect the effects of recent and earlier C&NS to be different. This constitutes a complementary, albeit more direct and transparent, alternative to Thakral and Tô's test of adaptive reference dependence.

Settings, Data and Methodology

The taxi industry has been of great interest to economists due to its special work arrangement, which enables empirical tests of various competing economic theories. In particular, Singapore's taxi market has attracted considerable attention from researchers (Ho et al., 2017; Chou, 2002; Agarwal et al., 2015, 2017, 2018), thanks to not only data availability but also several unique features of the market. The typical arrangement in Singapore is for the taxi operator to lease cabs to drivers using specific rate schemes, and drivers freely choose how long to work each day. One feature of Singapore's taxi industry that differentiates it from the extensively studied NYC yellow cab market is that it is common for customers to book taxi services via telephone, SMS, the internet, and mobile apps, whereas in NYC cabs are mostly hailed on the street[2]. With the arrival of ride-hailing services

[2] A number of for-hire vehicle companies in NYC provide prearranged transport service, but the number of trips completed by these companies is relatively small compared to yellow cab trips (Taxi and Limousine Commission Factbook, 2016). Recently, several mobile apps such as Curb have been developed to allow yellow and green cabs in the city to accept bookings (see https://www.theverge.com/2016/3/23/11294758/curb-app-taxi-hail-uber-nyc-verifone).

such as Uber and Grab, customers in Singapore are becoming more accustomed to booking their rides, and taxi operators are increasingly promoting their own booking systems to remain competitive[3]. In essence, Singapore's taxi industry is a combination of traditional taxi services and a modern ride-hailing platform.

We exploit a novel dataset provided by a major taxi operator in Singapore, which covers 3 months of street hail trips and taxi bookings by more than 30,000 drivers and comprises 34 million observations for the period December 1, 2016–February 28, 2017. To the best of our knowledge, this is the first taxi dataset of this size used in a research study that contains detailed information about not only street hail trips and taxi bookings, but also C&NS.

We employ fixed effects regression as our main methodology, utilizing multiple sets of fixed effects to absorb unobserved market conditions and driver characteristics. We also leverage the rich set of features present in our dataset to address various endogeneity concerns. Our estimates are robust, in terms of both direction and magnitude, across a wide range of specifications. We conduct a placebo test to further confirm that our results are not driven by unobserved market factors or selection. Lastly, although our main specification is linear, we have conducted extensive specification checks that allow for various forms of non-linearity to confirm that our results are not driven by functional assumptions.

As a robustness check, we also employ an instrumental variables approach, using the free taxicab count near the pickup location and around the booking time as exogenous source of variation affecting the C&NS rate. The rationale and the results of this approach are discussed in Appendix E. Since the exogeneity test fails to reject the exogeneity of C&NS, we choose to use fixed effects regression as our main approach.

Main Results, Interpretation, and Economic Significance

Our analysis shows that drivers work longer and earn more per hour following C&NS, apparently seeking to compensate for the loss and to reach the income target. Longer work hours and increased productivity can reverse the negative impact of cancellations, leading to higher income for the shift. However, they can only fully offset the negative impact of no-shows on shift income, due to more time wasted by no-shows. Interestingly, working longer and increasing productivity are substitutable rather than complementary devices, and are chosen by taxi drivers in their own favor: More experienced drivers, with better job search skills than less experienced ones, tend to work more diligently to increase their productivity; solo drivers, with a more flexible schedule than sharing drivers, tend to work more hours. Furthermore, these effects are strong in the first hour after a C&NS and fade away afterward. Interestingly, the C&NS effects are strongest when cumulative income is moderate and

[3]See Agarwal et al. (2018) for a study on the interaction between taxi bookings and ride-hailing platforms in Singapore.

close to the average shift income, and become weaker and insignificant when the income level is too high or too low.

Our results, collectively, suggest income targeting behavior to be the explanation for the C&NS effects on labor supply. The alternative explanation that C&NS effects are driven by lower fatigue or lower disutility of work after a C&NS is unlikely because cumulative income level has a significant moderating effect on the C&NS effects. There is no reason for the effect of fatigue to be different at different cumulative income levels. On the contrary, the income target theory provides a consistent explanation for such phenomenon: If the driver is too far below the target, a small earnings shock from a C&NS may not meaningfully change the chance of achieving the target as much as when the driver is very close to the target; if the driver is too far above the target, a C&NS will not move him from the gain domain to the loss domain and thus he has no incentive to change his behavior. Moreover, according to our conversations with drivers and the feedback from the taxi operator, C&NS are commonly viewed as a nuisance rather than an opportunity for a breather. Vehicle utilization and earnings rate increase after C&NS, and hence it is unlikely that the drivers catch a short break following C&NS. We also rule out the possibility of immediate pickups or other events immediately following C&NS, rather than the C&NS themselves, causing the change in labor supply. The most plausible interpretation of the C&NS effects is income targeting: C&NS lower the driver's total earnings given the same duration of work, which motivates him to work longer and harder to reach the daily target.

The magnitude of the C&NS effects is economically significant: A C&NS is associated with 31% to 33% reduction from the mean hazard rate of stopping work at a given time. This is equivalent to the effects of additional 55 minutes of work, or additional 48 Singapore dollars (SGD, 1 SGD = 0.7 USD during the data period) of realized earnings having on the decision to stop (Table 3, Column (7)). From our personal interactions with drivers and the taxi operator, C&NS are frequent enough, with an average occurrence rate of 1-2 times every week, to be a significant concern in their work. More importantly, our paper uses C&NS as an example for unanticipated earnings shocks, and C&NS are far from being the only unanticipated nuisance that taxi drivers encounter daily. Even though Farber (2015) claims that unanticipated earnings only account for a small proportion of the total variation in NYC taxi drivers' daily income, subsequent studies sometimes reach contrary findings. Both Thakral and Tô (2018) and Martin (2017) find evidences in support of income targeting—also among NYC taxi drivers—by employing more flexible specification. The relevance of unanticipated earnings may depend on context, and drivers at certain time and in certain places may experience more of such shocks than others. There are several reasons why Singapore's taxi drivers may find unanticipated earnings more prominent: the complex topography of the city, the existence of a booking system, the competition from a public transport network that regularly expands, etc. Moreover, the proportion of taxi bookings is increasing rapidly over years, making C&NS more important to the drivers day by day.

Contributions

Our paper makes three contributions to the literature on daily labor supply of flexible-hour workers. The first is to provide a new, cleaner test and new, more compelling evidence for reference-dependent labor supply. Our results provide strong evidence for reference-dependent preference among Singapore's taxi drivers, which is not a surprise given the mixed findings from numerous studies in similar contexts. The novel aspect of our results is that we obtain such findings by exploiting an *unanticipated* source of random income shocks, C&NS, that are naturally encountered by workers in the market to identify the income reference effect. This constitutes a direct and stronger test for the class of reference-dependent preference models described by Kőszegi and Rabin (2006) or any models that allow the reference point to adjust to workers' anticipation. This extends the literature, because the interpretation of our results is free of concern about the relative strength of anticipated versus unanticipated variation in income or the exact process by which the reference point is formed.

In addition, our independent variables, C&NS, are not only unanticipated, but also *externally* determined—since they are passengers', not drivers', decisions—which enables a better identification strategy. Previous studies use two common approaches to identify reference dependence. The first is to look for negative correlation between hours of work and average daily wage, as in Camerer et al. (1997). Oettinger (1999) and Farber (2005) criticize this approach on three grounds: (1) the use of realized earnings, which are an equilibrium outcome, as a proxy for wage rate is questionable; (2) wages are not constant within a day, and using average daily wage may constitute a misspecification; and (3) construction of the wage rate, by dividing total earnings by total hours of work, is prone to measurement error and division bias. The second approach is to examine the correlation between intra-day earnings and the hazard of stopping work throughout the day. Although this approach reduces concern about measurement error and division bias, and is able to account for the dynamic nature of earnings and labor supply, it is not entirely free of potential endogeneity issues. Intra-day income, in the form of either cumulative earnings up to a certain point in time, or total earnings in a specific hour into the shift, is an outcome variable jointly determined by market demand and workers' behaviors, and is likely correlated with unobserved market factors and workers' characteristics that may also contribute to workers' decision to stop working.

In contrast, the shocks we use in this paper—decisions made by agents on the other side of the market without any direct interaction with workers—are external, and hence unlikely to be subject to confounding factors due to unobserved worker heterogeneity. The shocks may still be correlated with market conditions, however, and to address this issue we leverage our novel dataset to construct a rich set of control variables—arguably the most detailed set of controls in this line of study so far. Even in this regard, our approach still tends to be more reliable because the set of confounding market factors that pose a threat to our identification strategy must be those that influence two different kinds of decisions by two different agents: passengers' decisions to cancel or not show up and workers' decisions to continue supplying labor. This set is likely to be much smaller than the set of market factors that influence two related outcomes by the same agent, workers' earnings and labor supply, that may bias estimates using the intra-day income approach.

Our second contribution is that our results provide clean and convincing evidence for the adaptive nature of the reference point. This complements findings in the growing literature on the path of reference points over time (DellaVigna et al., 2017; Thakral and Tô, 2018). We find that the timing of income shocks matters: A recent C&NS has a stronger effect on labor decisions, and the effect lasts for no more than 2 hours. In this regard, our results are most closely related to those of Thakral and Tô (2018), who find that recent earnings have stronger effects on the hazard of stopping work than distant earnings in the same day. In one of our specifications, we account for Thakral and Tô's effects by controlling for individual earnings during a different time period in the shift, but C&NS effects persist. Therefore, though similar in nature, Thakral and Tô's model does not entirely explain our results. It also shows that different sources of income shocks may change the reference in different ways, or at a different speed, and more research should be done on this subject.

Our third contribution is that we investigate not only the extensive margin of labor supply—the decision to stop working—but also the intensive margin: how long to work and how much effort per unit of time. Previous studies have treated the intensive margin, especially effort, as a nuisance because it is difficult to observe and may constitute a confounding factor. However, if reference dependence motivates workers to supply more labor to hit their income target, there is no particular reason for them to favor one dimension of labor supply over the other—and, naturally, increases in both margins are expected. Because the source of income shocks that we use, C&NS, is externally determined, it is unlikely that the intensive margin will be a confounding factor. Moreover, our novel dataset allows us to construct multiple measures that directly and indirectly capture different dimensions of effort and investigate the intensive margin in detail. We first show that subsequent rate of earnings, an outcome that is increasing in effort, is positively affected by C&NS, which indicates that C&NS and income targets also have an effect on the intensive margin of labor supply. We subsequently examine other proxies for the intensive margin—breaks, idleness, driving speed, and bidding behavior—and observe similar patterns in all of these dimensions.

Our paper also makes several contributions to other strands of research. Notably, it is the first to study workers' behavioral responses to C&NS in the service sector. This is related to the literature on the impacts of C&NS (Moore et al., 2001; Patrick and Puterman, 2008; Norris et al., 2014; Feldman et al., 2014), but our focus is on the behavioral effects rather than the operational aspects of C&NS. The paper is also related to the literature on service quality management (Cohen et al., 2018), but our interest is in how workers cope with C&NS rather than customer satisfaction and retention.

The rest of the paper is organized as follows. Section II reviews related literature. Section III presents the background of Singapore's taxi industry and an overview of the data. We develop a stylized model of daily labor supply in Section IV, report the main results in Section V, and conclude in Section VI.

II. Literature Review

Our research is related to several strands of literature. First, the paper contributes to the growing literature on productivity and performance under stress and negative shocks. We focus on a common source of negative shocks in the service sector, C&NS, and how they affect service providers—in our case, taxi drivers. Second, our research complements various studies in operations research and management that have examined the operational impacts of C&NS, especially on hospital and clinic appointments. Third, the taxi industry and taxi drivers have been studied extensively in the labor supply literature, and our paper draws several connections to this literature.

A. Coping under stress and/or negative shocks

Negative shocks can generate pressure, frustration, change in motivation, or other emotional responses and affect performance. These responses can be negative, which exacerbates the situation even further, especially if the original impact of the shock is large. For instance, in the context of factory production, Cai et al. (2018) find that machine breakdowns decrease worker productivity on the following day, which is likely to be caused by negative emotions and increased cautiousness. However, if the shock is modest, it can sometimes be managed and coped with, such that the negative effects can even be reversed. In sports, Berger and Pope (2011) analyze 18,000 professional basketball games and find that being slightly behind at half-time actually increases the winning percentage. The authors attribute this phenomenon to the goal-setting behaviors and motivational factors that seem to be consistent with prospect theory. In a laboratory experiment study, Buser (2016) finds that losing a competition tends to increase willingness to seek further challenges, and this effect is more prevalent in men than women; it is worth noting that Singapore's taxi drivers are predominantly male, with only 2% female drivers. Cai et al. (forthcoming) study the gender gap in *gaokao* (China's competitive and high stake national college entrance examination) and find that male students outperform females on the actual examination relative to their performance on the mock examination. Interestingly, they also find that male students outperform themselves on the actual examination, relative to the mock examination, if their mock examination score is slightly lower than the cutoff point.

The focus of our study is on a commonly encountered negative shock, C&NS, in a market with a large number of small independent service providers. Our findings are consistent with the results in this literature: C&NS are small negative shocks that taxi drivers encounter throughout the day, and can actually improve drivers' willingness to take on more job opportunities and increase their productivity.

B. Cancellations and no-shows

C&NS have been studied in other contexts, most notably in hospital and clinic appointments. A strand of the literature has studied the determinants of C&NS decisions by customers, including weather, age, transportation difficulties, new versus returning patients, and modes of scheduling, among others (Norris et al., 2014). Moore et al. (2001) quantify the revenue shortfall due to no-shows at a family practice clinic as 3%-14%. The operations research literature has examined how to optimize booking and scheduling systems to reduce the effect of C&NS (Feldman et al., 2014; Patrick and Puterman, 2008).

Our paper contributes to this literature by providing evidence that the effects of C&NS can go beyond their impact on the operational flow of the system; they may even change how human actors in the system behave. This also suggests that without taking into account the behavioral responses from human actors, any estimates of the operational effects of C&NS are likely to be biased. For example, if taxi drivers try to offset the negative impacts of booking C&NS, the taxi operator may not be able to observe any changes in system-wide earnings or utilization, and could underestimate the true operational impacts of those actions. Our results highlight the need to take into account the behavioral effects of cross-side interactions when designing and evaluating platform performance.

C. Labor supply

The labor supply of taxi drivers has been studied extensively in labor economics. The time flexibility that taxi drivers enjoy, coupled with the high fluctuations in daily wages they experience, makes them ideal subjects for testing the implications of competing labor supply models. In their seminal paper, Camerer et al. (1997) find that the wage elasticity of work hours among NYC drivers is negative, which is at odds with neoclassical theory but consistent with income targeting behavior. Crawford and Meng (2011) formalize this idea with a structural model, building on Kőszegi and Rabin's 2006 concept of reference-dependent preference, and find the presence of both income targeting and hour targeting behaviors among NYC drivers. Farber (2005) criticizes Camerer et al.'s econometrics and proposes a discrete choice stopping-time model for labor supply. He finds that hours of work affect decisions to stop work, but—consistent with neoclassical theory—income does not. Farber (2015) exploits a large dataset with over 100 million taxi trips in NYC and finds that even though income slightly affects labor supply decisions, hours of work are still the more important factor, and neoclassical effects seem to dominate income targeting effects. Martin (2017) uses similar data and finds evidence of not only loss aversion, but also diminishing sensitivity to loss among taxi drivers in NYC and San Francisco, which is consistent with prospect theory (Kahneman and Tversky, 1979).

The literature has evolved substantially over time both in methodology and data quality. The methodology has gradually moved away from ordinary least squares and instrumental variables regressions of working hours on wage at shift level (Camerer et al., 1997), which are prone to measurement errors, toward discrete choice models of labor supply decisions at trip level (Farber, 2005, 2015; Crawford and Meng, 2011; Martin, 2017). Researchers also increasingly leverage more complete and higher-quality data, thanks to the availability of large administrative datasets such as the NYC Taxi and Limousine Commission (TLC) dataset. A number of recent studies have also looked at app-based ride-hailing services such as Uber, Grab, and Lyft, using the large volume of data generated by these platforms and their ability to price trips dynamically. Chen and Sheldon (2015) find that U.S. Uber drivers work more during a price surge, which is consistent with neoclassical theory; Chen et al. (2017) study the benefits of work flexibility among Uber drivers; and Hall et al. (2017) combine Uber data and TLC yellow cab taxi data to study short- and long-run effects of fare changes on drivers' wages and labor supply. However, since the focus of this literature has been on testing whether taxi drivers' labor supply decisions are consistent with neoclassical economic theory or income targeting theory, it has not investigated how taxi drivers respond to the adverse actions of customers, which is the focus of our paper.

Our paper draws on this literature in two ways. First, the data we use are similar to those used in the most recent work in this literature, with one notable difference: Our data also include bookings, cancellations, and no-shows, which enable us to employ similar methodology for data analysis and shed new light as well. Second, we also focus on labor supply, and in line with findings from this literature, we carefully control for neoclassical labor effects and income targeting effects when necessary. We also contribute to this literature in two ways. First, we provide compelling evidence for income targeting effects among taxi drivers in a new context–Singapore's taxi industry. Second, we identify additional determinants of taxi drivers' labor supply: booking cancellations and passenger no-shows.

III. Industry Background and Data Description

A. Industry background

Singapore is a city-state with 721 sq km in land area and 5.6 million residents as of 2017. As a popular tourist destination, the city receives more than 15 million visitors each year. Singapore has one of the world's most extensive transportation networks, with 200 km of rail network and 357 bus routes in operation and total bus and rail ridership of 7.2 million per day. The total number of taxicabs at the end of February 2017 was 26,986, amounting to around 4,820 cabs per million residents. In contrast, New York City, with 783 sq km in land area and a population of 8.6 million, has 13,237 yellow taxicabs in operation[4], for an average of 1,540 cabs per million residents.

There are seven taxi operators and two main ride-hailing services (Grab and Uber) in Singapore.[5] Only Singaporean citizens with a Taxi Driver's Vocational License are allowed to work as taxi drivers. Drivers can join either as hirer drivers, who lease cabs directly from the operators, or as relief drivers, who arrange the lease privately with hirers. Daily rental fee varies with the model and age of the vehicle, and typically falls between 70 SGD and 120 SGD.

All cabs in Singapore are fitted with electronic meters. Taxi fare structures are regulated but highly variable, with various surcharges based on time and location of the trip. For standard taxis, the base fare consists of (1) a flag-down fare of 3.2 to 3.9 SGD, (2) a variable distance rate of 22 to 25 cents for every 400 m in the first 10 km and for every 350 m thereafter, and (3) a waiting time fare of 22 to 25 cents for every 45 seconds. Time-based surcharges can be as high as 50% of the meter fare between midnight and 6:00 a.m. Location surcharges range from 2 to 5 SGD. Bookings incur a fixed fee, which varies with pick-up time, taxi type, and how far in advance the booking is made. For normal taxis, the booking fee is 3.3 SGD during peak hours (6:00 p.m. to midnight every day and 6:00 a.m. to 9:30 a.m. on weekdays) and 2.3 SGD during non-peak hours; however, it can be as high as 20 SGD for advance booking with Chrysler cabs. The booking fee is added to the trip bill after the trip is completed. Bookings can be made through a number of channels, including mobile app, SMS, hotline, and web portal. In our sample, mobile apps are by far the most popular way to book a cab, accounting for more than 57% of bookings.

The booking fee is a nontrivial portion of the total fare. The typical booking fee (3.3 SGD) equals 19% of the total fare for an average booking trip (17.53 SGD, inclusive of the booking fee) or 23% of the trip fare exclusive of the booking fee. Furthermore, there is no penalty for C&NS, which makes street hail trips much more cost effective for passengers, except for the uncertainty of these trips. As a result, if a passenger, while waiting for the booking, sees an empty taxi passing by, it is likely that she will jump on the taxi and forgo the booking. By doing so, not only does she avoid paying the nontrivial booking fee, but also shorten the waiting time. Calling back to cancel the booking is optional, and hence this can result in either a cancellation or a no-show. Taxi drivers operate independently; therefore, many C&NS incidents are due to *random* encounters between the waiting

[4]NYC added street hail livery service (Boros Taxi) in 2013, with 7,676 vehicles in operation at the end of 2015, but these taxis can only pick up passengers in the outer boroughs.

[5]Grab acquired Uber's Southeast Asia business in March 2018. During the period in our sample, the two companies operated independently.

passenger and an empty taxi on the street.

The taxi operator employs a booking bidding system. The booking process proceeds as follows. First, a passenger makes a booking via one of the available channels and provides relevant information such as pick-up location, drop-off location (for app bookings only), and requested pick-up time (for advance bookings only). Second, the taxi operator broadcasts the booking request to a number of nearby drivers. Third, drivers bid for the booking by stating how quickly they can reach the passenger by choosing among 4-6 minutes, 6-8 minutes, and 8-10 minutes. The driver with the best bid wins the booking and drives to the pickup location. During this process, the passenger can cancel the booking at any time and the driver is informed of the cancellation instantly. Otherwise, the driver proceeds to the indicated pickup point and, if the passenger shows up, drives him/her to the destination. There is no compensation to drivers for C&NS.

B. Data description

Each observation in the data corresponds to either a street hail trip or a booking. For street hail trips, we observe the start time and end time, pickup and destination postal code, travel distance, total fare, vehicle ID, and driver ID. For bookings, we observe the booking time, requested pickup time, booking channel, booking status, ID of the assigned vehicle, and, if the booking is completed, all information on the trip mentioned above. Bookings, with completed, failed, cancelled, or no-show status[6], take up 27% of total observations: 76% of all bookings are completed, 13% are cancelled, 10% are failed, and slightly more than 1% are no-shows.

The data include 24,828,442 street hail trips and 9,114,421 bookings made between December 1, 2016 and February 28, 2017. During that period, 33,849 drivers were working and 17,468 vehicles were in operation.[7] Of the drivers, 98% are males, 78% are over the age of 50, and 84% have worked for the company for more than two years. Around 11% drivers are solo drivers, 35% share a cab with one other driver, 30% with two other drivers, and 24% with at least three other drivers.

Following the literature (Farber, 2015; Agarwal et al., 2015; Martin, 2017; Chen and Sheldon, 2015), we cluster trips and bookings into shifts. A shift is defined as a series of trips and bookings less than 6 hours apart by the same driver. In other words, any gap between two consecutive trips or bookings of more than 6 hours marks the end of one shift and the beginning of the next.

We conduct several data-cleaning steps to remove irrelevant or erroneous observations and outliers (see Appendix A). In total, 31,108,572 observations, or 92% of the original data, survive this procedure. Of these, 76.51% are street hail trips, 21.51% completed bookings, 484,448 (1.56%) cancelled

[6]"completed" indicates completed bookings, "failed" indicates bookings for which the system failed to find a cab to assign to them, "cancelled" indicates bookings that are cancelled by the passenger, either before or after the system assigns a cab to them, and "no-show" indicates bookings in which the passenger did not show up.

[7]A driver can drive multiple vehicles, although the great majority of drivers stick with one vehicle.

bookings, and 129,363 (0.42%) no-show bookings. An average street hail trip takes 16.02 minutes and earns the driver 12.85 SGD, while an average booking trip takes 20.12 minutes and earns 17.57 SGD, inclusive of booking fees (Panel A, Table 1).

[Insert Table 1 here]

Summary statistics for shifts are reported in Panel B of Table 1. We identified 2,122,256 shifts in total. On average, a shift lasts for 8.6 hours and earns the driver 200 SGD. During a shift, an average driver is idle (not on fare) around one-half the time, and receives 11.2 street hail trips and 3.2 bookings. Singapore taxi drivers' time utilization is on par with Uber and Lyft drivers, and far above that of traditional taxi drivers in the U.S. (Cramer and Krueger, 2016). The average number of cancellations and no-shows in a shift is 0.23 and 0.06, respectively—or in equivalent terms, a driver on average encounters a cancellation once every 4-5 shifts and a no-show once every 16 shifts. Half of the shifts start between 4:00 a.m. and 10:00 a.m., and around one-third start in the late afternoon or early evening (4:00 p.m. to 10:00 p.m.). The other 14% of shifts start between 10:00 a.m. and 4:00 p.m., and a small percentage start in the late evening or early morning (10:00 p.m. to 4:00 a.m.).

We focus on four outcome variables: probability of ending a shift after each trip, remaining time, remaining income, and remaining idle percentage. The first two variables measure driver's labor supply, and the last two measure driver's productivity. The probability of ending a shift refers to whether the current trip is the last trip of a shift. The remaining time is the time drivers stay on the job after each trip, i.e., the period from the end time of a trip to the end of the corresponding shift. The remaining income is the total income drivers receive during the remaining time. The remaining idle percentage is the percentage of time the driver is not with a passenger during the remaining time. The average probability of stopping is 14.6%; the average remaining time after each trip and booking is 4.73 hours; average remaining earnings are 108.74 SGD; and the average remaining idle percentage is 53.83%.

In Appendix B, Figure A1, the dashed lines plot the average number of completed trips in each hour by day of the week. Patterns for the five weekdays are similar to each other, with three peaks: in the morning around 8:00 a.m., early afternoon around 2:00 p.m., and evening around 10:00 p.m. The pattern for weekends is relatively flat throughout the day after reaching a peak around 10:00 a.m. The solid lines plot the rate of C&NS over total bookings in each hour by day of the week. On weekdays, we observe a small peak in C&NS at 8:00 a.m., and during weekends the peak is at around 3:00 a.m. Throughout the week, the rate of C&NS fluctuates around 8%.

We also create a panel of driver-hours by aggregating trips and bookings made by the same driver in the same day and hour. For trips and bookings that span multiple hours, the fares and distances are prorated to each of the hours by the time spent in the respective hour. We refer to this panel as the "hour-level data." The advantage of using hour-level data over trip-level data is that the time intervals in this panel are uniform, and therefore it is easier to conduct dynamic analysis that relates current behavior to previous states. The disadvantage of using hour-level data, compared to trip-level data, is that drivers are constantly moving, and it is difficult to make use of their location information. Another complication of using hour-level data is censoring—i.e., the fact that drivers are unlikely to start and stop work exactly at the beginning and the end of the clock hour, and hence the first and last hours of work are usually shorter than the other hours. Due to shorter duration, C&NS are less likely to occur in the first and last hours. By definition, last hours are highly correlated with drivers' decisions to stop work and, in turn, their earnings. As a result, including these hours in the analysis will lead to correlation between C&NS and drivers' decisions due to data censoring rather than to any behavioral motive. To avoid this spurious correlation, we drop all censored observations when using hour-level data. We also use the indicator for last *full* hour of work—rather than the indicator for the last hour of work—as the outcome of interest when working with hour-level data.

We also make use of real-time taxi location data to construct additional variables to supplement the above datasets. All taxis in Singapore are equipped with an in-vehicle unit (IVU) that records the cab's status and GPS coordinates every 10 to 15 seconds. This dataset contains over three billion IVU readings. Using real-time status and location data, we are able to compute the number of nearby vehicles, the time and distance to pickups for all bookings, and the duration and timing of all the breaks drivers take.

C. Model-free evidence

Table 2 shows the relationship between C&NS and drivers' subsequent labor supply decisions and earnings. Without any C&NS, on average, 15.0% of drivers will stop work after each hour. If any C&NS occurs in the hour, the percentage of drivers stopping work after the hour decreases by 3.3 percentage points (ppts) to 11.7%. The difference is significant at the 1% level. If they continue to work after a C&NS, average earnings in the next hour are 26.35 SGD, which are 2.14 SGD (s.e. 0.017) more than the average earnings of 24.21 SGD in hours when they do not encounter any C&NS.

[Insert Table 2 here]

[Insert Figure 1 and Figure 2 here]

Figures 1 and 2 break down the above statistics by clock hour of the day (the left panel in both figures) and by hour into the shift (the right panel). The left panel of Figure 1 shows the proportion of drivers who stop work after each of the 24 hours in the day, separately for hours with C&NS (dashed line) and without C&NS (solid line). Both lines follow a similar pattern: There is a peak in the early morning around 2:00 a.m.-4:00 a.m., probably due to night-shift drivers ending work, and another peak in the afternoon around 3:00 p.m.-5:00 p.m. when the day-shift drivers end work. Throughout the morning, from 7:00 a.m. to 12:00 p.m., the lines stay relatively flat and low, since most day-shift drivers have just started their shifts and are unlikely to quit so early. What is interesting is that apart from the morning period—when very few drivers quit—the dashed line stays consistently below the solid line, which means that throughout the day, the proportion of drivers who stop work is lower after the hours with C&NS. The right panel of Figure 1 shows the proportion of drivers who stop work after each hour since the start of a shift, separately for hours with C&NS (dashed line) and without C&NS (solid line). Similar to the left panel, the dashed line stays consistently below the solid line, which means that throughout the shift, drivers are less likely to stop work after they encounter C&NS.

Figure 2 shows average hourly earnings in each hour of the day (the left panel) and each hour into the shift (the right panel), separately for hours with C&NS in the previous hour (dashed line) and without any C&NS (solid line). Earnings are higher between 6:00 p.m. and 10:00 a.m., which are the periods with taxi surcharges. In both panels, the dashed line stays consistently above the solid line, which means that throughout the day, average earnings in the hours following a C&NS are higher than average earnings in the hours without a prior C&NS.

The above statistics and figures demonstrate a significant negative correlation between C&NS and the decision to stop work, as well as a significant positive correlation between C&NS and subsequent earnings. In other words, drivers are less likely to stop work and tend to earn more following C&NS. In subsequent sections, we will develop regression models that control for various sources of confounding factors and potential endogeneity and present evidence to argue that these correlations reflect a causal relationship between C&NS and driver behavior.

IV. Theory

This section presents a simple discrete-time model of daily labor supply with income targeting behavior, and discusses its testable implications. Proofs of the propositions are in Appendix C.

Discrete-time model of labor supply

Suppose that a driver's day of work is divided into two periods. At the end of the first period, the driver can choose to stop working. If working in period j, the driver receives an anticipated earnings of a_j and experiences a disutility of c_j due to work as well as a random utility shock ε_j. There is also an unanticipated earnings shock of u, which is realized at the end of the first period. The driver has an income target of t for the day, and exhibits loss aversion with respect to this target: Each unit of earnings above the target brings an additional utility of η, while each unit of earnings below the target generates a disutility of $\lambda\eta$, with $\lambda > 1$. The driver's utility if he stops at the end of the first period and if he continues is, respectively, as follows:

$$V^{stop} = a_1 + u + l(a_1 + u - t) - c_1 + \varepsilon_1$$
$$V^{work} = a_1 + a_2 + u + l(a_1 + a_2 + u - t) - c_1 - c_2 + \varepsilon_1 + \varepsilon_2$$

with $l(\cdot)$ is the loss-gain utility, $l(i) = \eta i$ if $i \geq 0$ and $l(i) = \lambda \eta i$ if $i < 0$.

PROPOSITION 1: *The probability of stopping work is weakly increasing with the unanticipated earnings u.*

The intuition for the results in Proposition 1 is as folows: When the earnings of the first period are at a level such that the driver will be below target if he stops, but above target if he continues, an additional unit of unanticipated earnings would increase the stopping utility more than it increases the continuing utility, reduce the net mean utility of continuing work, and increase the probability of stopping. Proposition 1 is the main testable implication of the model.

Endogenous target

We now consider rationally-formed income target, i.e., target that is equal to the expected earnings during the day. Formally speaking, we define a labor-supply strategy as a pair $(t, d(\cdot))$ consisting of an income target t and a decision rule $d(u)$ that specifies whether to quit given each realization of the unanticipated earnings u. A labor-supply strategy is said to be a rational targeting equilibrium (RTE) if the decision rule is optimal given the target, and the target is equal to the expected earnings given the decision rule. We can prove that an RTE exists, but may not be unique.

PROPOSITION 2: *If* (t^*, d^*) *is an RTE under the set of parameters* (a_1, a_2, c_1, c_2)*, then* $(t^* + \delta, d^*)$ *is an RTE under the set of parameters* $(a_1 + \delta, a_2, c_1, c_2)$*.*

In other words, in response to an anticipated increase in earnings, a driver can increase the target by the same amount, leaving him equally far from the target as before, and hence keeping the optimal labor supply decision rule unchanged. As a result, variation in anticipated earnings has no effect on the stopping decision at the end of the first period. This is in stark contrast with the effect of unanticipated earnings, as shown in Proposition 1.

It should be emphasized that the results in Proposition 2 are meant to be illustrative rather than comprehensive, and we do not expect them to generalize to other settings. There are at least two plausible scenarios where they fail: fixed target and diminishing sensitivity. With fixed target, the target does not adjust to offset the increase in anticipated earnings, making it easier for the driver to reach the target and stop early. With diminishing sensitivity, marginal utility will depend on the level of income even within the gain (loss) domain, and hence, an increase in anticipated earnings, which changes the income level, may change the labor supply decisions. However, Proposition 2 does demonstrate that the relationship between anticipated earnings and daily labor supply is difficult to interpret without knowing how the target is formed.

Effort

Suppose that, instead of receiving fixed anticipated earnings a_1 and a_2, the driver can choose the effort[8] level to earn e_1 and e_2, but pay the cost $c(e_1, e_2)$ that is increasing and convex in both e_1 and e_2. The driver's utility if he stops at the end of the first period and if he continues is, respectively,

$$V^{stop} = e_1 + u + l(e_1 + u - t) - c(e_1, 0) + \varepsilon_1$$
$$V^{work} = e_1 + e_2 + u + l(e_1 + e_2 + u - t) - c(e_1, e_2) + \varepsilon_1 + \varepsilon_2$$

PROPOSITION 3: *The optimal effort in the second period, if the driver chooses to continue working, is decreasing with the unanticipated earnings u.*

The intuition for the results in Proposition 3 is as folows: Due to loss-aversion, the marginal utility of earnings is higher when the income is below the target, while effort cost does not depend on income level. Hence, the driver will exert more effort if falling short of the target. A big enough unanticipated earnings shock may push the driver from the loss domain to the gain domain, and as a result, reduce the effort. When the unanticipated shock is at a moderate level, the optimal strategy is to spend enough effort to reach the target, and the marginal effort cost is between the two marginal earnings utility. In such cases, even a small increase in unanticipated shock will push the driver to the gain domain, where the marginal earnings are lower than the marginal effort cost, and the drivers will have the incentive to reduce his effort level, creating a negative relationship between effort level and unanticipated shock.

The econometrics of earnings and daily labor supply

The previous discussion shows that with income targeting, daily labor supply can be affected by unanticipated earnings, but not necessarily by anticipated earnings. If so, how should we interpret the results of a regression of labor decisions on realized earnings, a combination of both anticipated and unanticipated earnings, and/or earnings shocks? This subsection presents a reduced form regression model and investigates what its estimates mean.

[8]For taxi drivers, effort can be having less break time, paying more attention to potential passengers, willing to take more bookings and street hails trips, willing to drive to far-away destinations, etc.

Let y denote the labor decision, u and a unanticipated and anticipated earnings, x an observed unanticipated earnings shock (e.g. C&NS), i realized earnings, ε and ω unobserved labor supply factors and unanticipated earnings shocks. The econometrician observes only y, x and i. For the ease of analysis, assume all unobserved shocks are independent, and all variables have zero mean and follow the following relationships: $y = \beta u + \varepsilon, \quad u = \gamma x + \omega, \quad i = u + a.$

PROPOSITION 4: *(a) The OLS estimate of y on i converges to* $\beta \frac{V(u)}{V(u)+V(a)}$

(b) The OLS estimate of y on x converges to $\beta\gamma$

(c) The OLS estimates of y on i and x converge to $\beta \frac{V(\omega)}{V(\omega)+V(a)}$ *and* $\beta\gamma \frac{V(a)}{V(a)+V(\omega)}$

Proposition 4 implies that the OLS estimate of realized earnings effect on labor supply is likely to underestimate the causal effect of unanticipated earnings because it is pulled down by the variation of anticipated earnings which may not have a causal relationship with labor supply. Moreover, when realized earnings are included together with a random earnings shock in a regression, the realized earnings effect may not fully absorb the effect of the earnings shock, even though the earnings shock is part of the realized earnings. As a result, it is difficult to interpret the coefficient of realized earnings: It does not capture the effect of unanticipated shocks, nor reflect the influence of anticipated earnings on labor supply. On the other hand, the coefficient of the random earnings shock is straightforward to interpret: It is a product of the effect of unanticipated earnings on labor supply and the effect of the shock on earnings.

V. Models and Results

In this section, we outline our regression models and discuss the implications of the estimation results. We first look at labor supply and examine (1) the decision to stop work after a C&NS and (2) how long drivers continue to work after a C&NS. We then study drivers' productivity after a C&NS by examining (3) the idle percentage and (4) average hourly wage after each trip. We follow with the discussion on the dynamics and heterogeneity of these effects, the net impact on shift income, and possible mechanisms for these effects. Competing explanations are discussed and ruled out at the end of the section. For space reasons, we report results on (1) and (3) in the main text and relegate those on (2) and (4) in Appendix D.

To identify the effects of C&NS, we exploit the fact that C&NS are passengers' decisions and unlikely to be affected by driver behavior. However, there may still be endogeneity issues if passengers base their decisions on driver characteristics, or if unobserved confounding factors are present, such as market conditions, that affect both the occurrence of C&NS and drivers' labor supply and productivity decisions. We argue that the first scenario is unlikely due to institutional settings. Specifically, passengers have access to very little information about the driver during the booking process: After making a booking, passengers are informed of only the vehicle's plate number and the estimated time of arrival. Since the great majority of the drivers stick with one vehicle, we include driver fixed effects in all regressions to control for driver-related and vehicle-related factors such as perceived unlucky plate numbers. Longer estimated time of arrival may lead to more C&NS, and we use distance and time to pickup point to control for this factor. Furthermore, as previously discussed, booking fees are nontrivial, and many C&NS are due to passengers hailing a random empty taxi that happens to pass by while waiting for the booking.

To address the second problem—i.e., the existence of confounding factors—we employ fixed effects and a set of controls to absorb the impacts of those factors. The main concern is demand and supply conditions. In addition to adding into the regression demand density, measured as the number of jobs (bookings and street hails) within 1 km and within 1 hour of the focal trip, and supply density, measured as the number of vehicles within a 500 m radius and 3 minute time window, we control for these factors by a rich set of time and location fixed effects: (1) We include date fixed effects to control for daily variation in demand and supply and absorb factors such as public holidays, school holidays, tourist season, etc. (2) We add hour of day fixed effects to control for within-day variation in market conditions, especially the difference between peak and non-peak hours. In addition, we use different sets of hour fixed effects for different days of the week, for weekday holidays, and for weekend holidays to capture distinct patterns of the taxi market on workdays, off days, and holidays. (3) We also include postal code fixed effects or hour $\times$ day of week $\times$ zone fixed effects to control for spatial or spatiotemporal differences in taxi demand and supply across the city. There are 312 zones, for an average area of 2.3 sq km for a zone. This is a relatively fine spatial division, and we expect little within-zone variation in unobserved confounders that may bias our estimation. The hour $\times$ day of week $\times$ zone fixed effects also control for weather and air quality conditions. The 120,000 postal code fixed effects provide even finer control for spatial heterogeneity, since in Singapore each postal code is associated with a unique building, and each building usually has a designated pickup point for taxis. As a result, our estimates of C&NS effects are identified out of the within-zone driver-specific portion of C&NS variation that is uncorrelated with date and hour.

We also argue that residual confounding factors, if any, are likely to understate the magnitude of our estimates. One concern is that the difficulty of navigating in unfamiliar areas can also increase passenger waiting time—and hence the likelihood of C&NS—and at the same time hinder the driver's search efficiency and overall earnings. However, this is likely to create more cancellations due to longer waiting time, while decreasing driver productivity due to higher search frictions, and hence shorter working hours, given the findings in the literature that classical labor supply behavior dominates income targeting behavior (Farber, 2015). Another concern is that during morning peak hours there can be an oversupply of cabs in central business district (CBD), and passengers in that area may be more likely to cancel bookings due to the abundance of cheaper alternatives. However, an oversupply of cabs also means higher competition, as well as possible traffic congestion, and hence is likely to decrease drivers' earnings and willingness to work. The factors that increase C&NS are likely to be the factors that lower passengers' valuation of bookings and/or taking a taxi in general relative to other substitutes, and hence should hurt drivers. Our findings are the opposite: Drivers seem to have higher earnings and longer working time after encountering C&NS. Note that most of the aforementioned factors should have been absorbed by our time and location fixed effects, but even in unlikely cases in which some factors are not captured, our estimates can still be viewed as the lower bounds of drivers' behavioral responses to C&NS.

A. Impact on labor supply

Following prior literature on taxi drivers' labor supply (Farber, 2005, 2015; Agarwal et al., 2015; Chen and Sheldon, 2015), we develop a hazard model to analyze drivers' decisions to stop work. At the end of each trip or booking, a driver must decide whether to continue working or end the shift by comparing the benefits and costs of continuing against those of stopping. Following Farber (2005, 2015), we formulate the decision as a binary probability model and assume a linear form for this function[9], as follows:

$$Quit_{it} = \beta_c I_{it}^{cancel} + \beta_{ns} I_{it}^{noshow} + \alpha_i + f(H_{it}) + g(I_{it}) + \mathbf{X_{it}}'\gamma + u_{it} \tag{V.1}$$

where i denotes a driver and t denotes a taxi trip or booking. $Quit_{it}$ is a binary variable: $Quit_{it} = 1$ if trip or booking t is the last trip/booking in a shift by driver i, and $Quit_{it} = 0$ otherwise. I_{it}^{cancel} and I_{it}^{noshow} are indicator variables for the cancellation and no-show status of the current booking, i.e., $I_{it}^{cancel} = 1$ if trip t by driver i is cancelled, and 0 otherwise; and $I_{it}^{noshow} = 1$ if trip t by driver i is a no-show, and 0 otherwise. α_i is the driver fixed effect, which accounts for not only drivers' preferences with respect to work and non-work activities, but also their individual propensity to receive and accept a booking. $f(H_{it})$ is a flexible function of the cumulative hours of work, which controls for the baseline hazard rate of stopping at different point in time in the shift. $g(I_{it})$ is a flexible function of the cumulative income and controls for driver's income targeting behavior. $\mathbf{X_{it}}$ is the set of observable factors that affect stopping decisions. It includes a set of time and location fixed effects and other

[9]We use a linear probability model instead of a logistic model to estimate this discrete choice equation for a similar reason: Inclusion of driver and time fixed effects renders logistic estimation computationally costly. We also conduct a robustness check from a logistic regression on a subsample of drivers and obtain robust results (available from the authors).

market factors to account for future earnings opportunities; these variables are used by drivers to form their expectations about future working conditions.

Results of the linear probability model are reported in Table 3. Each of the seven specifications in the table uses a different set of control variables and fixed effects. The first specification, in Column (1), controls for cumulative working hours and driver fixed effects. Cumulative hours are positively correlated with the decision to stop work, since the marginal disutility of work increases with time. Regarding driver's characteristics, it is likely that hard working, motivated drivers bid more and receive more bookings than others, and hence are subject to more C&NS. After controlling for these factors, regression results estimate that a cancellation is associated with an average decrease of 2.2 ppts in the hazard rate of stopping work, and a no-show with an average decrease of 2.3 ppts. At the average hazard rate of stopping work of 6.6%, this represents a one-third reduction.

[Insert Table 3 here]

Specification (2) adds date fixed effects and hour of day fixed effects for each day of the week. The concern is that different days, a different time of the day, and day of the week may exhibit different demand and supply patterns, and may also be correlated with C&NS. Date fixed effects will capture long-term trend and seasonality in demand and supply; the hour $\times$ day of week fixed effects would be able to capture the variation pattern of demand and supply within a week—for example, the differences between off-peak hours and peak hours, and the differences between weekdays and weekends. The estimated magnitudes of C&NS effects do not change much. This suggests that most of the confounding factors related to timing of demand and supply are likely to have been captured by the previous sets of controls and fixed effects.

Specification (3) adds postal code fixed effects to control for spatial heterogeneity. The concern is that different locations may differ in demand and supply density or search friction, which affect both drivers' labor supply and the rate of C&NS. As noted previously, in Singapore each building is assigned a unique postal code and has a designated taxi pickup point, so postal code fixed effects are a very fine control for spatial heterogeneity, and therefore are able to absorb the differences between two drivers picking up customers at two adjacent buildings. Including this set of fixed effects actually increases the magnitude of the estimated cancellation and no-show effects to 2.6 ppts. This is consistent with our previous argument that if spatial heterogeneity, such as demand and supply density or search friction, is the concern, our estimates are likely to understate rather than overstate the true effect of C&NS.

Specification (4) controls for the interaction between time and location by including hour $\times$ day of week $\times$ zone fixed effects. Due to the large number of postal codes (120,000), we cannot interact time with postal code fixed effects. This set of fixed effects would be able to flexibly capture spatiotemporal demand and supply patterns, such as the fact that demand tends to move from residential areas to the business district on weekday mornings and in the opposite direction during the late afternoon. The magnitude of the C&NS effects slightly decreases to 1.9 ppts. In total, more than 52,000 additional fixed effects are added to the regression, but the changes in the main estimates are minimal. This suggests that location and time interactions cannot explain the observed relationship between C&NS and drivers' labor supply decisions.

Specification (5) adds a large set of control variables to address several concerns about the exogeneity of C&NS. First, there may be irregular demand and supply factors that are not captured by the existing time and location fixed effects. To address this, we include a host of weather conditions (temperature, humidity, rain, air pollution), together with proxies for demand and supply density in nearby neighborhood at the end of the trip/booking. Second, some drivers may have predetermined motivation to work harder on certain days, and they may be more aggressive than usual in finding jobs and bidding for bookings, which gains them more earnings opportunities but also more C&NS. To control for this, we add the number of previous bookings as a control, since more aggressive drivers should receive more bookings, and if this behavior is a source of bias, including the number of previous bookings will attenuate the C&NS effects. Lastly, we include the duration and distance to pickup point to absorb possible selection bias by passenger due to waiting time and pickup conditions. Adding these variables to the regression slightly increases the estimated effects of C&NS to 2.0 and 2.1 ppts compared to the results in Specification (4). Adding these sets of controls incrementally or separately also results in similar estimates. Therefore, we are confident that the above endogeneity concerns have minimal effects on our results.

Specification (6) allows for non-linear effects of cumulative hours, in the form of a flexible cubic function, to account for varying marginal effect of hours throughout a work shift. At -2.1 ppts and -2.3 ppts, the new estimates are not meaningfully different from the previous specifications. We have experimented with other forms of nonlinearity (e.g. higher-order polynomials, multi-step function, and a combination of both), and the results remain robust.

Specification (7) controls for cumulative income effects. As we have discussed in Section 3, if the income target is fixed, we would expect the realized earnings to soak up all the effects of unanticipated earnings. On the other hand, if the target is endogenous or adaptive, we would not expect the realized earnings to fully capture the effects of unanticipated shocks, since its effect is pulled down by the lower, even non-existent, effects of anticipated earnings. The estimated C&NS effects are almost identical to those in Specification (6), suggesting the fixed target theory does not explain our results. Consequently, our results can be taken as an evidence in favor of an endogenous and/or adaptive reference point over a fixed reference point.

To allow for even more flexibility in capturing duration dependence of the hazard rate, we run separate regressions for separate time intervals in the shift. This allows for the effects of not only cumulative hours but also of other factors to change over time. As noted by Thakral and Tô (2018), these regressions are equivalent to local weighted regressions (Cleveland and Devlin, 1988) with a uniform weight over a fixed time window, allowing for non-parametric identification of general smooth function over time. Table 4 reports the regression results for each of the hour from the sixth to the tenth hour into shift. Using smaller windows (30 tutes and 10 minutes) gives similar results (available from the authors). The estimates are, once again, robust to the function assumption about the duration dependence of the hazard rate. This not only improves the confidence in the validity of our specification, but also provides strong evidence for the claim that C&NS are random exogenous events over time. Furthermore, these results highlight an additional advantage of our approach—using random earnings shocks—over the usual approach of using cumulative income, since cumulative income is highly correlated with working hours, making it difficult to disentangle the two effects. Table 4, Specification (6) controls for earnings in each of the hour prior to the trip and booking, to account for Thakral and Tô (2018)'s within-day adaptive reference point. The magnitude of the C&NS effects is nearly the same as those in Specification (5) of the same table.

[Insert Table 4 here]

In summary, when regressing on different sets of controls and fixed effects, estimated C&NS effects on drivers' decisions to stop work remain consistently negative, and the magnitudes vary from 1.9 ppts to 2.6 ppts. This negative relationship between C&NS and the decision to stop work cannot be entirely explained by time effects, location effects, drivers' aggressive bidding, or passengers' selective C&NS decisions. Therefore, it is likely to reflect a causal relationship between C&NS and drivers' labor supply.

Another measure of labor supply is the duration a driver continues working on the shift after each trip or booking.

$$Remaining\_time_{it} = \beta_c I_{it}^{cancel} + \beta_{ns} I_{it}^{noshow} + f(H_{it}) + g(I_{it}) + \mathbf{X_{it}}'\gamma + \alpha_i + u_{it} \tag{V.2}$$

$Remaining\_time_{it}$ is the duration driver i continues working after trip/booking t, i.e., the duration from the end of t to the end of the corresponding shift. Other variables are the same as in Equation (V.1).

Appendix D, Table A1 reports estimates for eight specifications of Equation (V.2), each of which uses a different set of control variables and fixed effects. While the dependent variable in Table 3 reflects the short-term relationship between C&NS and labor supply—i.e., how C&NS affect the decision to stop immediately after the trip or booking—the dependent variable in Table A1 captures the lasting effects of C&NS on labor supply. Specification (8) combines all of the aforementioned control variables in the same regression. A cancellation is associated with an increase of 4.2 minutes in the remaining working time, and a no-show is associated with an increase of 5.9 minutes, which are about one-quarter to one-third of an average trip's duration. The effect of cancellation on the remaining working time is equivalent to the effect of driving 10 minutes less or earning 8 SGD less, and the effect of no-show is equivalent to driving 14 minutes less or earning 11 SGD less. Thus, it seems that remaining on the shift for a longer duration is another way by which Singapore's taxi drivers respond to C&NS.

B. Impact on productivity

In this section, we present estimates of the effects of C&NS on drivers' subsequent productivity, measured by hourly earnings after a trip or a booking.

$$Y_{it} = \beta_c I_{it}^{cancel} + \beta_{ns} I_{it}^{noshow} + \alpha_i + f(H_{it}) + g(I_{it}) + \mathbf{X_{it}}'\gamma + u_{it} \tag{V.3}$$

Y_{it} is driver i's subsequent earnings rate, defined as the total fare earned after a trip/booking divided by the total duration remaining in the shift after the trip/booking. Table 5 reports the estimates for various sets of fixed effects and control variables.

[Insert Table 5 here]

Hourly earnings following a cancellation are on average 16 to 88 cents higher than those following a completed trip or completed booking. After a cancellation, the driver is not only busier, but also earns better wages, suggesting that he is becoming more productive in his job.

The effects of no-shows are not always statistically significant or positive, and the magnitudes are smaller than those of cancellations. One explanation is that a driver has to spend much more time trying to reach the no-show passenger, which is ultimately wasted time since it generates no fare and hence negatively affects the driver's earnings.[10] The driver may also experience this negative effect with a cancellation, but with smaller magnitude due to less time wasted, and hence the productivity-increasing effect dominates and we observe a statistically significant and positive effect of cancellation on subsequent hourly wage.

Appendix D, Table A2 reports the effect of C&NS on idle percentage. The specification with the full set of controls reveals that a cancellation is associated with a reduction of idle percentage, while

[10]The taxi company requires that drivers wait at least 2 minutes before driving away, unless they call the passenger to confirm that he or she is not coming. Passengers' phone numbers are not shown to drivers, and vice versa, and calls are routed through a centralized system.

a no-show is associated with an increase in idle percentage due to more time wasted driving to the pickup point and waiting for the passenger.

The above results suggest that C&NS can have two opposite effects on productivity: The negative impact due to lost time is direct and immediate, while the positive effect due to increased work hours and increased job search efficiency is indirect and takes time to materialize. To disentangle these effects, we turn to a dynamic model specification in which we explicitly include contemporaneous and lagged C&NS. We expect contemporaneous C&NS to absorb the negative effects, and lagged C&NS to single the positive effects out.

C. Dynamic effects of cancellations and no-shows

To examine the dynamic effects of C&NS, we aggregate trip-level data to construct a panel of driver-hours. First, each trip or booking is assigned to a clock hour according to its start and end time. Trips that span multiple clock hours are divided into segments that fit into the respective clock hours, and their fares are prorated to the duration. We next aggregate the data by summing up the fare and trip duration assigned to each clock hour, driver by driver. We then regress hourly earnings on the number of C&NS in the current hour as well as in the previous hours. We expect that the effects of C&NS in the same hour partially captures the negative effect on productivity due to lost time, whereas the effects of C&NS in previous hours capture the positive effect of these adverse events on the driver's productivity.

$$Y_{ih} = \sum_{s=0}^{p} \beta_{c,s} N_{i,h-s}^{cancel} + \sum_{s=0}^{p} \beta_{ns,s} N_{i,h-s}^{noshow} + \mathbf{X_{ih}}'\gamma + \alpha_i + u_{ih} \tag{V.4}$$

Y_{ih} is the total fare that driver i earned in clock hour h, $N_{i,h-s}^{cancel}$ and $N_{i,h-s}^{noshow}$ are the number of C&NS that driver i encounters in clock hour $h-s$ (i.e., s hours before h), and α_i and $\mathbf{X_{ih}}$ are defined as before.

[Insert Table 6 here]

Table 6 reports the dynamic effects of C&NS on hourly earnings for p up to 2. Specification (1) includes the number of C&NS in the current hour only. The results show reduced earnings in the same hour of C&NS, but the magnitude is much larger for no-shows: A cancellation is associated with 3 cents reduction, while a no-show is associated with a 2.8 SGD reduction, which is about 12% of hourly wage.

Specification (2) includes the number of C&NS in the previous hour as additional explanatory factors for hourly income. The results show an increase of 80 cents and 57 cents in current-hour earnings for each cancellation and no-show in the previous hour. The effect of previous-hour no-shows is in stark contrast to that of current-hour no-shows, and we attribute this difference to the fact that no-shows in the previous hour do not affect the driving time in the current hour, and hence do not crowd out any productive time in the current hour. Thus, this effect is likely to capture drivers' behavioral responses. However, these behavioral responses are not able to fully offset the negative effect of no-shows on the same hour's earnings, which leads to an overall small but negative impact on hourly earnings following a no-show (Table 5).

Specification (3) includes an additional set of extra lags for C&NS. The effects of C&NS from 2 hours ago on current-hour earnings are small and statistically insignificant at the 5% level. This suggests that the driver's response to C&NS is not permanent, and tends to last for no more than 2 hours.

The dynamic nature of the C&NS effects suggests a role for an adaptive reference point. This is similar to the results in Thakral and Tô (2018), in which the authors find recent earnings to have stronger effects on labor than earnings earlier in the shift[11], and attribute such phenomenon to the drivers slowly updating their income targets based on recent earnings. Similarly, if the drivers slowly adjust their targets to the events of C&NS, an earlier C&NS will have more time to be considered and incorporated into the drivers' current target, and hence does not represent as much of an unexpected shock as a more recent C&NS does. As a result, the C&NS effects fade away over time, consistent with the results in Table 6.

It is interesting to compare our results with similar situations in different contexts. As noted before, Cai et al.'s 2018 study of the effects of machine breakdowns on worker productivity on subsequent days finds that work interruptions decrease subsequent productivity due to negative emotional reactions and increased cautiousness. In contrast, drivers in our study are motivated to work more diligently after a C&NS. This difference may be due to the nature of the work—e.g., the driver's work is flexible and independent—or the severity of the adverse events, since a C&NS only costs drivers several minutes of work, while machine breakdowns can put workers out of work for an entire day. Our results show that the effects of adverse conditions on productivity can be context dependent, and are not always negative.

D. Effect heterogeneity

The results in previous sections suggest that taxi drivers may react to C&NS in two ways: by prolonging working hours and increasing productivity. In this section, we examine how these two responses interact by looking at different groups of drivers.

[11] We also observe similar recency effects of earnings on labour supply, but only up to the eighth hour into the shift (see Table 4, Column (6)).

D.1. Solo drivers versus sharing drivers A vehicle may be shared by multiple drivers; the typical arrangement is for two drivers to share one vehicle and work different shifts in the day. With shared vehicles, drivers face time constraints, since they must transfer the vehicle to the other driver at a predetermined time. However, there are also drivers who do not share their vehicle with any other driver, and presumably have more flexibility in scheduling their shifts. We expect sharing drivers to have a higher cost of prolonging their shifts due to time constraints, and hence may not be able to extend their working hours as much as solo drivers do when needed. Because of this, a sharing driver will be more likely to resort to increasing productivity to compensate for the loss from C&NS, in contrast to a solo driver.

Table 7, Columns (1) and (3) report the estimates for Equations (V.2) and (V.3) with added interactions between solo driver dummy and booking status. Estimates in the first column show that solo drivers tend to increase their working time following a C&NS more than sharing drivers. This is consistent with the hypothesis that solo drivers have lower cost of extending their working hours when needed due to their scheduling flexibility.

Interestingly, the effect of the interaction between solo drivers and no-show/cancellation on average remaining hourly wage is negative, which suggests that solo drivers do not strive to increase their productivity as much as sharing drivers do. The difference is 6 cents, and statistically significant. One explanation is substitutability between extending working hours and increasing productivity as a response to an adverse event. Specifically, for solo drivers, having the ability to extend their working hours with less stringent constraints reduces their need and motivation to work harder each hour to cope with C&NS.

[Insert Table 7 here]

D.2. More experienced versus less experienced drivers Table 7, Columns (2) and (4) report estimates for Equations (V.2) and (V.3) with added interactions between booking status and an indicator for drivers who joined the taxi company before 2014. The indicator is used as a proxy for experience. Drivers who joined earlier are presumably able to accumulate more knowledge and skills, which translate into better productivity adjustment when needed. The results in Column (4) show that the increase in average wage following a cancellation for drivers who joined before 2014 is 24 cents, which is more than 50% higher than the increase for drivers who joined after 2014.

In terms of labor supply, the increase in the remaining work time following a cancellation for more experienced drivers is on average 2.6 minutes shorter than less experienced drivers. This result is also consistent with labor supply adjustment and productivity adjustment being substitutable for each other as a response to adverse events. More experienced drivers, who can better adjust their productivity after a cancellation or no-show, may not have to rely on extending their working hours to cope with such adverse events as much as less experienced drivers do.

The two heterogeneous effects suggest that working longer and increasing productivity are substitutable, rather than complementary, devices when drivers respond to C&NS. Drivers who have an advantage with one device tend to employ it more, and thus have less motivation to squeeze the other.

E. The moderating effect of cumulative income

Table 8 reports the estimated C&NS effects during the 9th hour of the shift and for five separate income intervals. The effects are strongest and most significant when the income is in the range 150-200 SGD. The effects decrease in magnitude and become insignificant when the cumulative income is either too low or too high, while the baseline hazard rate does not change much. This is consistent with income-targeting behavior: When cumulative income is too low, there is very low chance for the driver to reach the target, and hence it reduces the incentive to work more when drivers encounter adverse earnings shocks. On the other hand, when income is too high, it is likely that the driver has exceeded the target and extra earnings do not change the marginal utility of income. This also disproves the hypothesis that C&NS effects are driven by the disutility of working: There is no reason why the marginal disutility of work changes with the level of cumulative income.

[Insert Table 8 here]

F. Net effect on total shift income

As discussed previously, C&NS may have an immediate negative effect on drivers' earnings due to the unproductive time spent driving to pickup points and waiting for passengers; subsequently, however, drivers tend to make up for these losses by working longer and more diligently. The net effect on total income is not obvious: Can drivers make up for all the loss that C&NS incur, and do they ever overcompensate for the negative effects? Table 9 reports the relationship between C&NS and total shift income. The estimates suggest that taxi drivers tend to overcompensate for cancellations and total income tends to be 3.4 SGD higher in shifts with some cancellations. Taxi drivers can also fully compensate for no-shows, but the total impact on shift income is much muted: The shift income is 70 cents higher on average in shifts with some no-shows.

[Insert Table 9 here]

G. How drivers increase the rate of earnings after cancellations and no-shows

In most markets, in the short-run and from the perspective of workers, wage is usually fixed and exogenously determined. However, the nature of the taxi industry enables drivers to have some room to adjust their rate of earnings if needed. Their working conditions are flexible in terms of both time and location, and when motivated, they may reduce their break time, pay more attention to street-hail passengers, bid for more bookings, drive to locations with more earnings opportunities, etc. These actions may incur more effort per unit of time, but under heightened motivation and/or increased pressure to hit an income target, drivers may engage in these actions to improve their income.

Table 10 shows that C&NS are associated with less break time[12] and more jobs received in the next hours. Specifically, if drivers encounter a cancellation (no-show) in the previous hour, on average they take 0.5 (0.8) minutes less break time, and receive 0.04 (0.06) more jobs. Columns (4) and (5) break down the increase in the number of jobs received into bookings and street hail trips. Interestingly, a cancellation (no-show) is associated with an increase of 0.09 (0.10) in the number of bookings, but a decrease of 0.04 (0.03) in the number of street hails that a driver receives in the next hour. It suggests that drivers get more booking after C&NS, perhaps because they become more aggressive in bidding for the bookings, which crowds out the number of street hail trips they can complete. However, the increase in bookings outweighs the decrease in street hail trips, and hence, the total number of jobs increases after C&NS, which helps the drivers achieve higher duration with passenger—0.7 to 0.6 minutes more with passenger on board, according to Column (1)—and better earnings (drivers on average earn more on booking trips). This is also consistent with the results from a trip-level regression of the status of the next trip on C&NS indicator of the current trip[13]: The immediate next trip is 7 to 10 ppts more likely to be a booking following a C&NS. Note that the taxi operator employs a bidding system and there is no compensation of any kind to drivers experiencing C&NS. This suggests several strategies drivers can employ to improve their earnings after a C&NS: reducing break time, being more willing and aggressive to bid for bookings, and, in general, increasing their productive time with passengers on board.

[Insert Table 10 here]

Table 11 estimates the effects of C&NS on the distance, duration and speed that drivers take to find the next job. The results show that, after C&NS, drivers tend to drive faster, and take not only less time but also shorter distance to find a new job. The increase in speed after a cancellation can be partially explained by the fact that the drivers are on the road at the time of cancellation rather than stopping at the destinations as in completed trips. However, for no-shows, drivers also need to stop at the pickup locations, so it is fair to compare speed after a no-show and after a completed trip; and the increase in

[12] Break time is calculated by aggregating the duration between consecutive "break" readings in the real-time location and status data.

[13] The dependent variable of the regression is a binary variable which equals 1 if the next job is a booking, and 0 otherwise. The 2 main independent variables are I_{it}^{canel} and I_{it}^{noshow}, as defined above. The regression includes controls for driver fixed effects, date fixed effects, hour of day$\times$day of week$\times$zone fixed effects, demand and supply density. It is omitted for brevity.

speed after a no-show suggests that it is not due to locational factors, but drivers' behavioral response. Less time and shorter distance after a C&NS to a new job can result from either the driver being in a high demand area or the driver being more efficient in job search. Since our model already controls for demand conditions, it is more likely due to the latter. This increase in speed and reduction in search time and distance contribute to the improvement in drivers' productivity following C&NS.

[Insert Table 11 here]

H. Alternative explanations

Immediate pickups and other events that follow C&NS

C&NS may lead to events and circumstances that differ from those following completed trips. For example, drivers may see potential customers on the way to the booking, and could turn around and pick them up right after a C&NS. To rule out incidental effects from these events, we restrict our sample to trips and bookings in which drivers searched for a passenger for at least 3 minutes or 1 km after the trip/booking. This rules out the effects of a driver finding a customer right after a C&NS or of any event that follows a C&NS, since after 3 minutes or 1 km of driving, in both cases—C&NS and a completed trip—drivers end up in the same circumstance: on the road searching for passengers. Table 12 shows that this restriction does not affect the direction or magnitude of C&NS effects in any meaningful way and demonstrates that our results are not by-products of any events that follow a C&NS, but rather are likely to be directly caused by a C&NS. Stricter restrictions (5 minutes and 2 km) yield the same results.

[Insert Table 12 here]

Drivers' ability to avoid C&NS

Some drivers may be better at predicting and avoiding C&NS than others, and this ability may be correlated with unobserved characteristics that affect their labor decisions. We argue that this is unlikely in our setting. First, all regressions control for driver fixed effects, so any driver-specific differences in ability should have been absorbed by the fixed effects; hence this ability only matters to our results if there is variation within drivers: The same driver may be better at C&NS prediction at a certain time or a certain location than at other times or locations. Variation along the temporal dimension is unlikely, because the majority of drivers in our sample are highly experienced (84% have worked for the company for at least 2 years) and we do not expect their taxi-related ability to vary significantly over the course of three months. Variation along the spatial dimension is also unlikely, because Singapore is a small city-state with a highly developed traffic network and urban landscape, so most taxi drivers are able to become familiar with most areas after a short time on the job.

Second, we conduct several robustness tests in which we allow driver fixed effects to vary from day to day and location to location, and the results still hold. Table 13, Columns (1) and (2), allow driver fixed effects to vary over time by interacting fixed effects with month and with day of week. The interaction with month is to account for a possible learning effect over time, while the interaction with day of week is to account for the possibility that some drivers are more familiar with the weekday market than the weekend market, and vice versa. Column (3) allows driver fixed effects to vary across regions, to account for the fact that some drivers may be more familiar with certain regions than others. All of the estimates for C&NS effects on stopping work in these three columns are similar to results in previous sections. Column (4) estimates C&NS effects for trips and bookings from CBD, an area that must be very familiar to all the drivers and in which we expect little heterogeneity in C&NS-predicting ability. Cancellations reduce the hazard rate of working by 1.78 ppt (s.e. 0.04), which represents a 38% decrease from the average hazard rate in the CBD region (4.7%). In comparison, as reported in Column (5), cancellations reduce the hazard rate in non-CBD region by 2.78 ppt (s.e. 0.06), or a 30% decrease from the average non-CBD hazard rate of 9.2%. These results show that differences in drivers' ability to predict and avoid C&NS do not explain C&NS effects on labor supply.

[Insert Table 13 here]

Drivers' unobserved plan

Drivers may have unobserved plans and may seek bookings with destinations that are convenient for their plans. The results in previous sections where we allow the driver fixed effects to vary with time and locations partially address this issue: Time and location are likely to capture a major portion of the variation in drivers' plans. We also utilize a portion of the bookings for which the passengers do not specify the destination at the time of booking, and hence it is unlikely that the drivers can plan ahead of these bookings. Table 13, Column (6) shows that the hazard rate of stopping work after such a booking decreases by 1.5 ppt (s.e. 0.0007) and 1.4 ppt (s.e. 0.0008) after a C&NS, representing a 37% and 34% drop from the average hazard rate of 4.03% among these bookings. The C&NS effects are still present and even slightly stronger when drivers are less able to plan ahead of the bookings. Thus, drivers' unobserved plans are not a plausible explanation for the effects of C&NS on labor supply.

Serial correlation in C&NS

C&NS may have correlation with itself over time; if so, encounters with C&NS may inform drivers about more (fewer) C&NS in the remaining part of their shifts if the serial correlation is positive (negative). As reported in Table 14, the data show positive but small serial correlation in hourly rate of C&NS after having partialled out hour of day, day of week, and date fixed effects, with first-order autocorrelation being only 0.225 (s.e. 0.023). More importantly, most of the autocorrelation comes from the 5 am to 2 pm period, during which C&NS effects are small, while autocorrelations from 2 pm to 10 pm and 10 pm to 5 am, when most stopping decisions are made for day-shift and night-shift drivers, and also when C&NS effects are the strongest, are much smaller and insignificant—0.053 (s.e. 0.043) and -0.019 (s.e. 0.049), respectively. Positive serial correlation in C&NS would actually strengthen the implications of our results, because knowing that there are more C&NS to come, drivers' motivation must be even stronger to keep them on the job despite the negative shocks. Nonetheless, the serial correlation is too small or insignificant to explain our results, especially during the time period in which our results show the most significant effects.

[Insert Table 14 here]

C&NS as an informative signal about market conditions

C&NS may be correlated with market conditions, and drivers may use them as a forecast for subsequent work. As we have discussed extensively in previous sections, the inclusion of a rich set of control variables and fixed effects would have been able to absorb most of the effects due to market conditions. In this section, we conduct a placebo test to further prove that the correlation with market conditions does not explain the C&NS effects on labor supply we have identified. We select half of the drivers as placebo drivers, and randomly match them with the other half. We then assign all C&NS encountered by placebo drivers to the corresponding drivers they have been matched to, as long as the timing of the C&NS falls within any of the matched drivers' shifts; these C&NS are called placebo C&NS. We then regress the decision to stop working on a list of dummy variables that indicate whether the driver has had any cancellation, no-show, placebo cancellation, or placebo no-show within the last hour. If market conditions are driving the C&NS effects, we would expect to see significant effects of similar magnitude from the placebo C&NS because market conditions affect all drivers in the market. Results in Table 15 show that this is not the case: Placebo effects—a decrease of 0.1 ppt (s.e. 0.09) in the hazard rate within 1 hour after a placebo cancellation and 0.19 ppt (s.e. 0.16) after a placebo no-show—are not significant at the 10% level and much smaller in magnitude than the real C&NS effects.

[Insert Table 15 here]

VI. Conclusion

In this paper, we investigate the effects of booking cancellations and passenger no-shows on taxi drivers' behaviors. Our analysis shows that following C&NS, drivers work longer and earn more per hour for the remaining work time of a shift, as if they strive to make up for the loss from such adverse actions, and the effects are strongest when the cumulative income is close to the average shift income. We also find that the increase in productivity after a C&NS is higher for more experienced drivers than for less experienced drivers, and the increase in work hour is larger for solo drivers than for sharing drivers. These results suggest that working longer and increasing productivity are substitutable, rather than complementary, devices in coping with C&NS. Furthermore, these effects are strong in the immediate following hour and fade away afterward.

This paper utilizes a novel source of unanticipated frequent shocks to identify the effect of within-day earnings on daily labor supply. By doing so, we provide a more direct, more convincing set of evidence for reference-dependent preference among taxi drivers in Singapore. More importantly, our results shed new light on the dynamics of reference point. The fact that the timing of C&NS matters, with the effects fading away over time, suggests that the reference point is adaptive to new events. The magnitude of the C&NS effects—a one third reduction in the hazard rate of stopping, equivalent to the effect of 48 SGD less in realized earnings—cannot be explained by the size of the equivalent loss in realized earnings and lost opportunity, even after we account for recent earnings in Thakral and Tô (2018)'s fashion. It could be that variation in realized earnings consists of both anticipated changes and unanticipated shocks, and sophisticated drivers would already have incorporated anticipated changes in their target and would appear non-responsive to anticipated changes. C&NS are most often unanticipated, and hence would draw a much large labor supply response from the drivers than an equivalent-size variation in realized earnings does. It could also be that C&NS represent a loss of potential earnings opportunity, and drivers may be more sensitive to potential loss than to realized gains when adjusting their target. As such, our paper highlights the need for more research on the formation of reference point, especially with regard to its interactions with anticipated and unanticipated shocks, and with potential and realized earnings.

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TABLE 1.—SUMMARY STATISTICS

Panel A: Summary statistics of completed trips						
	Obs	Mean	SD	Q1	Median	Q3
Street hail trips						
Trip fare (SGD)	23,801,832	12.85	7.33	7.45	10.90	16.40
Trip duration (mins)	23,801,832	16.02	9.52	8.98	14.43	21.12
Completed bookings						
Trip fare (SGD)	6,692,929	17.57	7.68	11.85	16.05	21.65
Trip duration (mins)	6,692,929	20.12	10.28	12.73	18.75	25.63
Completed trips						
Trip fare (SGD)	30,494,761	13.88	7.66	8.20	12.05	17.85
Trip duration (mins)	30,494,761	16.91	9.84	9.65	15.37	22.22

Panel B: Summary statistics of shifts						
	Obs	Mean	SD	Q1	Median	Q3
Shift income (SGD)	2,122,256	199.50	85.75	138.98	194.00	252.15
Shift duration (hours)	2,122,256	8.57	3.39	6.38	8.58	10.54
Shift wage (SGD/h)	2,122,256	24.16	8.45	19.52	23.96	28.42
Idle percentage	2,122,256	51.29	12.93	42.51	50.92	60.00
Number of street hail trips	2,122,256	11.22	5.57	7.00	11.00	15.00
Number of completed bookings	2,122,256	3.15	2.94	1.00	2.00	5.00
Number of cancellations	2,122,256	0.23	0.57	0.00	0.00	0.00
Number of no-shows	2,122,256	0.06	0.26	0.00	0.00	0.00
Start after 4am and before 10am	2,122,256	0.49	0.50	0.00	0.00	1.00
Start after 10am and before 4pm	2,122,256	0.14	0.34	0.00	0.00	0.00
Start after 4pm and before 10pm	2,122,256	0.33	0.47	0.00	0.00	1.00

Panel A reports the summary statistics of the trip-level data. Trip fare for booking trips includes booking fees; trip duration for booking trips excludes on-call time. Completed trips include both street hail trips and completed bookings. Panel B reports summary statistics of shift-level data. Each observation is a shift, defined as a series of consecutive trips and bookings by the same driver less than 6 hours apart.

TABLE 2.—MODEL-FREE EVIDENCE

	Hours with no C&NS	Hours with C&NS	Diff (s.e.)
Proportion stopping work	0.150	0.117	-0.0330***
			(0.0005)
Average earnings in next hour (SGD)	24.21	26.35	2.140***
			(0.0169)

The table reports summary statistics of the hour-level data. We exclude censored hours (the first and the last hours in each shift) and outliers (driver-hours with more than 5 cancellations or no-shows or with earnings more than 50 SGD). "Stopping work" means that the hour is the last *full* hour of the corresponding shift, i.e., the driver will end the shift at some time in the next hour. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 3.—HAZARD RATE OF STOPPING WORK

DV: Stop working (dummy)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cancellation (dummy)	-0.0224***	-0.0234***	-0.0260***	-0.0187***	-0.0201***	-0.0212***	-0.0211***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
No-show (dummy)	-0.0232***	-0.0225***	-0.0258***	-0.0185***	-0.0209***	-0.0225***	-0.0224***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Driver FE	Y	Y	Y	Y	Y	Y	Y
Date FE		Y	Y	Y	Y	Y	Y
Hour×day-of-week FE		Y	Y				
Postal code FE			Y				
Hour×day-of-week×zone FE				Y	Y	Y	Y
Additional Controls					Y	Y	Y
Controls for cumulative hours	linear	linear	linear	linear	linear	cubic	cubic
Controls for cumulative income							cubic
Marginal effects							
Cumulative hour (at 8 hours)	0.0228***	0.0234***	0.0236***	0.0236***	0.0241***	0.0305***	0.0230***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Cumulative income (at 200 SGD)							0.0441***
							(0.0008)
Mean hazard rate	0.0663	0.0663	0.0687	0.0687	0.0677	0.0677	0.0677
Observations	31,108,566	31,108,566	28,087,962	28,069,852	23,413,398	23,413,398	23,413,398
Clusters	33,667	33,667	33,667	33,667	33,650	33,650	33,650
R^2	0.102	0.124	0.140	0.143	0.144	0.147	0.149

Each column is a separate regression. An observation is a trip or a booking. The dependent variable for all columns is a binary variable ($Quit_{it}$) indicating if the trip or booking is the last of the shift. Additional controls consist of demand density, number of vehicles within 500 m, temperature, relative humidity, PM 2.5, an indicator for rain, on-call duration, distance to pickup, number of previous bookings, and an indicator for booking. For models with non-linear cumulative hour effect and/or cumulative income effects, the reported marginal effects are calculated for an increase of one hour at cumulative hours of 8 hours, and/or an increase of 100 SGD at a cumulative income of 200 SGD. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 4.—HAZARD RATE OF STOPPING WORK, BY HOUR INTO SHIFT

DV: Stop working (dummy)	(1) 6th hour	(2) 7th hour	(3) 8th hour	(4) 9th hour	(5) 10th hour	(6) 10th hour
Cancellation (dummy)	-0.0124***	-0.0158***	-0.0212***	-0.0285***	-0.0423***	-0.0419***
	(0.0011)	(0.0013)	(0.0017)	(0.0021)	(0.0027)	(0.0027)
No-show (dummy)	-0.0112***	-0.0139***	-0.0202***	-0.0262***	-0.0366***	-0.0361***
	(0.0018)	(0.0024)	(0.0028)	(0.0035)	(0.0044)	(0.0044)
Earnings ('00 SGD):						
first 5 hours						0.0169***
						(0.0017)
6th hour						0.0344***
						(0.0030)
7th hour						0.0601***
						(0.0030)
8th hour						0.0803***
						(0.0030)
9th hour						0.0521***
						(0.0032)
10th hour						0.0287***
						(0.0037)
Mean hazard rate	0.0517	0.0722	0.1011	0.1451	0.1925	0.1925
Observations	2,048,669	1,854,081	1,693,622	1,469,578	1,109,971	1,109,708
Clusters	33,119	32,685	31,971	30,747	28,602	28,602
R^2	0.211	0.239	0.265	0.289	0.314	0.316

Each column is a separate regression. An observation is a trip or a booking. The dependent variable for all columns is a binary variable ($Quit_{it}$) indicating if the trip or booking is the last of the shift. All specifications include driver fixed effects, date fixed effects, hour×day-of-week×zone fixed effects, demand density, number of vehicles within 500 m, temperature, relative humidity, PM 2.5, an indicator for rain, on-call duration, distance to pickup, number of previous bookings, and an indicator for booking. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 5.—EARNINGS RATE AFTER A TRIP/BOOKING (SGD/H)

DV: Subsequent earnings rate (SGD/h)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cancellation (dummy)	0.884***	0.581***	0.657***	0.359***	0.209***	0.190***	0.159***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
No-show (dummy)	0.404***	0.042**	0.135***	-0.169***	-0.242***	-0.268***	-0.300***
	(0.018)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)
Driver FE	Y	Y	Y	Y	Y	Y	Y
Date FE		Y	Y	Y	Y	Y	Y
Hour×day-of-week FE		Y	Y				
Postal code FE			Y				
Hour×day-of-week×zone FE				Y	Y	Y	Y
Additional Controls					Y	Y	Y
Controls for cumulative hours	linear	linear	linear	linear	linear	cubic	cubic
Controls for cumulative income							cubic
Marginal effects							
Cumulative hour (at 8 hours)	0.3957***	0.1511***	0.1512***	0.1487***	0.1677***	0.2899***	0.4919***
	(0.0027)	(0.0032)	(0.0032)	(0.0032)	(0.0034)	(0.0049)	(0.0068)
Cumulative income (at 200 SGD)							-1.2623***
							(0.0258)
Mean earnings rate	24.0	24.0	23.9	23.9	23.9	23.9	23.9
Observations	26,166,516	26,166,516	23,488,913	23,475,768	19,632,820	19,632,820	19,632,820
Clusters	33,634	33,634	33,632	33,632	33,615	33,615	33,615
R^2	0.359	0.435	0.441	0.445	0.448	0.449	0.451

Each column is a separate regression. An observation is a trip or a booking. The dependent variable for all columns is the subsequent earnings rate in SGD per hour, which is equal to the total income earned from the end of the trip till the end of the shift divided by the duration that the driver remains working. Additional controls consist of demand density, number of vehicles within 500 m, temperature, relative humidity, PM 2.5, an indicator for rain, on-call duration, distance to pickup, number of previous bookings, and an indicator for booking. For models with non-linear cumulative hour effect and/or cumulative income effects, the reported marginal effects are calculated for an increase of one hour at cumulative hours of 8 hours, and/or an increase of 100 SGD at a cumulative income of 200 SGD. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 6.—DYNAMIC EFFECTS OF CANCELLATIONS AND NO-SHOWS

DV: Hourly earnings (SGD)	(1)	(2)	(3)
Cancellations in current hour (count)	-0.0324**	-0.0804***	-0.0426**
	(0.0156)	(0.0173)	(0.0200)
No-shows in current hour (count)	-2.7567***	-2.7824***	-2.6767***
	(0.0267)	(0.0297)	(0.0346)
Cancellations in last hour (count)		0.8043***	0.8008***
		(0.0161)	(0.0185)
No-shows in last hour (count)		0.5661***	0.58526***
		(0.0302)	(0.0353)
Cancellations 2 hours ago (count)			-0.0349*
			(0.0185)
No-shows 2 hours ago (count)			-0.0585*
			(0.0363)
Observations	13,954,248	10,838,888	8,209,562
R^2	0.188	0.185	0.185

Each column is a separate regression. An observation is a driver-hour. All regressions control for driver fixed effects, hour of day fixed effects and date fixed effects. The dependent variable is the earnings received in the respective hour. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 7.—HETEROGENEITY

	Remaining time (mins)		Remaining wage (SGD/h)	
	(1)	(2)	(3)	(4)
Cancellation	7.540***	10.161***	0.632***	0.434***
	(0.206)	(0.409)	(0.010)	(0.020)
No-show	7.663***	10.896***	0.079***	0.017
	(0.393)	(1.029)	(0.019)	(0.049)
Cancellation×Solo driver	3.378***		-0.062**	
	(0.506)		(0.024)	
No-show×Solo driver	1.233		-0.023	
	(0.981)		(0.047)	
Cancellation×Join before 2014		-2.613***		0.238***
		(0.460)		(0.022)
No-show×Join before 2014		-3.461**		0.066
		(1.098)		(0.053)
Observations	31,108,572	31,108,572	26,511,772	26,511,772
R^2	0.633	0.633	0.423	0.423

Each column is a separate regression. An observation is a trip or a booking. All regressions control for driver fixed effects, date fixed effects, and hour of day fixed effects. Standard errors clustered by drivers in parentheses. The dependent variable in Columns (1) and (2) is the remaining time in minutes; the dependent variable in Columns (3) and (4) is the remaining average wage in SGD/h. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 8.—C&NS EFFECTS IN THE 9TH HOUR, AT DIFFERENT CUMULATIVE INCOME INTERVALS

DV: Stop working (dummy)	(1) 50-100 SGD	(2) 100-150 SGD	(3) 150-200 SGD	(4) 250-300 SGD	(5) 300-350 SGD
Cancellation (dummy)	0.0015	-0.0219***	-0.0288***	-0.0166*	-0.0068
	(0.0188)	(0.0074)	(0.0051)	(0.0086)	(0.0187)
No-show (dummy)	-0.0132	-0.0166*	-0.0264***	-0.0070	0.0542*
	(0.0293)	(0.0114)	(0.0081)	(0.0148)	(0.0330)
Mean hazard rate	0.1070	0.1310	0.1469	0.1397	0.1291
Observations	34,403	206,394	466,796	186,600	46,491
R^2	0.557	0.391	0.348	0.415	0.487

Each column is a separate regression. An observation is a trip or a booking. Each column limits the sample to the set of observations in the 9th hour of work and within the specified range of cumulative income. The dependent variable for all columns is a binary variable ($Quit_{it}$) indicating if the trip or booking is the last of the shift. All specifications include driver fixed effects, date fixed effects, hour×day-of-week×zone fixed effects, demand density, number of vehicles within 500 m, temperature, relative humidity, PM 2.5, an indicator for rain, on-call duration, distance to pickup, number of previous bookings, and an indicator for booking. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 9.—NET EFFECTS OF C&NS ON TOTAL SHIFT INCOME

	Shift income (SGD)	
	(1)	(2)
Cancellations (count)	12.273***	3.445***
	(0.114)	(0.070)
No-shows (count)	9.341***	0.680***
	(0.180)	(0.112)
Shift duration (hours)		18.933***
		(0.042)
Observations	2,073,595	2,073,595
R^2	0.517	0.800

Each column is a separate regression. An observation is a shift. Both regressions control for driver fixed effects, date fixed effects, and shift start hour fixed effects. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 10.—HOW DRIVERS IMPROVE EARNINGS AFTER C&NS

	(1) Duration with passenger (mins)	(2) Break duration (mins)	(3) Completed trips (count)	(4) Completed bookings (count)	(5) Street hail trips (count)
Cancellations in last hour (count)	0.7041***	-0.5102***	0.0409***	0.0902***	-0.0392***
	(0.0179)	(0.0161)	(0.0014)	(0.0009)	(0.0015)
No-shows in last hour (count)	0.5740***	-0.7992***	0.0610***	0.1011***	-0.0303***
	(0.0355)	(0.0319)	(0.0028)	(0.0018)	(0.0029)
Observations	13,038,157	13,038,157	13,038,157	13,038,157	13,038,157
R^2	0.178	0.145	0.111	0.196	0.138

Each column is a separate regression. An observation is a driver-hour. All regressions control for driver fixed effects, date fixed effects, and hour of day×day of week fixed effects. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 11.—DISTANCE, TIME AND SPEED TO THE NEXT JOB

	Distance to next job (km)		Time to next job (mins)		Speed to next job (km/h)	
	(1)	(2)	(3)	(4)	(5)	(6)
Cancellation	-0.9560***	-0.8704***	-4.7513***	-4.5632***	3.6285***	3.7225***
	(0.0151)	(0.0152)	(0.0624)	(0.0627)	(0.0965)	(0.0979)
No-show	-1.0752***	-0.9916***	-4.9562***	-4.7723***	0.7910***	0.8913***
	(0.0188)	(0.0189)	(0.0801)	(0.0807)	(0.0754)	(0.0762)
Demand density		-1.6811***		-5.1314***		-3.4812***
		(0.0095)		(0.0453)		(0.0817)
Vehicles within 500 m ('000)		3.9700***		7.1141***		2.9125***
		(0.0653)		(0.2729)		(0.4189)
Observations	27,769,530	27,459,427	27,769,530	27,459,427	27,769,257	27,459,154
R^2	0.198	0.200	0.048	0.048	0.014	0.014

Each column is a separate regression. An observation is a trip or booking. All regressions control for driver fixed effects, date fixed effects, and hour of day×day of week×zone fixed effects. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 12.—ROBUSTNESS CHECK: NO IMMEDIATE PICKUPS

	Search >3 mins		Search >1 km	
	(1) Stop working (dummy)	(2) Remaining wage (SGD/h)	(3) Stop working (dummy)	(4) Remaining wage (SGD/h)
Cancellation (dummy)	-0.0210***	0.637***	-0.0237***	0.708***
	(0.0006)	(0.0189)	(0.0006)	(0.0202)
No show (dummy)	-0.0177***	0.558***	-0.0200***	0.649***
	(0.0011)	(0.0324)	(0.0011)	(0.0340)
Observations	13,061,593	12,011,136	11,941,228	10,894,349
R^2	0.154	0.396	0.161	0.394

Each column is a separate regression. An observation is a trip or a booking. All regressions include driver fixed effects, date fixed effects, hour-of-day×day-of-week×zone fixed effects, cumulative hours, demand and supply density, weather conditions, number of cumulative bookings, on-call duration and distance. Dependent variable for Columns (1) and (3): dummy indicating the last trip/booking of the shift, for Columns (2) and (4): Average SGD earned per hour for the rest of the shift. Columns (1) and (2) restrict the sample to trips and bookings after which the status of the drivers is FREE for at least 3 mins. Columns (3) and (4) restrict the sample to trips and bookings after which the status of the drivers is FREE for at least 1 km. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 13.—ROBUSTNESS CHECK: VARIATION IN DRIVERS' ABILITY OVER TIME AND LOCATION

	(1) Includes driver × month FE	(2) Includes driver × day-of-week FE	(3) Includes driver × region FE	(4) CBD trips/bookings	(5) Non-CBD trips/bookings	(6) Bookings without destination
Cancellation (dummy)	-0.0220***	-0.0217***	-0.0232***	-0.0178***	-0.0278***	-0.0151***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0007)
No show (dummy)	-0.0199***	-0.0194***	-0.0220***	-0.0176***	-0.0228***	-0.0138***
	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0011)	(0.0008)
Mean hazard rate	0.0682	0.0682	0.0682	0.0471	0.0921	0.0403
Observations	30,604,181	30,603,703	30,603,545	16,231,776	14,372,368	2,973,200
R^2	0.145	0.156	0.165	0.102	0.174	0.145

Each column is a separate regression. An observation is a trip or a booking. Dependent variable: Stop working, i.e. the indicator for the last trip/booking of the shift. All regressions include date fixed effects, hour-of-day×day-of-week×zone fixed effects, controls for demand and supply density, weather conditions, number of previous bookings, on-call duration, and distance. Columns (4) and (5) include driver fixed effects. Column (1) includes driver×month fixed effects, Column (2) includes driver×day-of-week fixed effects, and Column (3) includes driver×region fixed effects. Columns (1), (2) and (3) use the full sample of trips and bookings. Column (4) uses only the subset of trips and bookings from the CBD. Column (5) uses the subset outside the CBD. Column (6) uses only bookings without destination information at the time of booking. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 14.—ROBUSTNESS CHECK: C&NS RATE SERIAL CORRELATION

	(1) All	(2) 5 am - 2 pm	(3) 2 pm - 10 pm	(4) 10 pm - 5 am
C&NS rate in previous hour	0.225***	0.221***	0.0533	−0.0194
	(0.0226)	(0.0334)	(0.0426)	(0.0489)
Observations	2,137	801	720	616
R^2	0.610	0.755	0.696	0.573

Each column is a separate regression. Data: time series of hourly nationwide C&NS rate (number of C&NS divided by number of bookings in each hour). Dependent variable: hourly nationwide C&NS rate. The top one percentile C&NS rates are dropped from all regressions. Estimated by OLS with date fixed effects and hour-of-day×day-of-week fixed effects. Column (1) uses the full sample. Column (2) uses only observations from hours from 5 am to 2 pm each day, Column (3) uses 2 pm to 10 pm, and Column (4) uses 10 pm to 5 am, respectively. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 15.—ROBUSTNESS CHECK: PLACEBO TEST

	(1)	(2)	(3)
Cancellation in last hour (indicator)	-0.0119***		-0.0119***
	(0.0004)		(0.0004)
No-show in last hour (indicator)	-0.0103***		-0.0103***
	(0.0008)		(0.0008)
Placebo cancellation in last hour (indicator)		0.0004	0.0005
		(0.0009)	(0.0009)
Placebo no-show in last hour (indicator)		-0.0003	-0.0003
		(0.0016)	(0.0016)
Observations	11,860,677	11,860,677	11,860,677
R^2	0.151	0.151	0.151

An observation is a trip or a booking. Data is sampled from a randomly selected set of 16,853 drivers. Estimated by OLS with driver fixed effects, date fixed effects hour-of-day×day-of-week×zone fixed effects, controls for demand and supply density, a cubic function of cumulative hours, weather conditions, number of previous bookings, on-call duration, and distance. Dependent variable: a dummy indicating the last trip/booking of the shift. Main regressors: dummies that indicate whether there is any cancellation/no-show/placebo cancellation/placebo no-show occurs within one hour prior to the end of the trip/booking. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

FIGURE 1. PROPORTION OF DRIVERS WHO STOP WORK: WITH AND WITHOUT C&NS

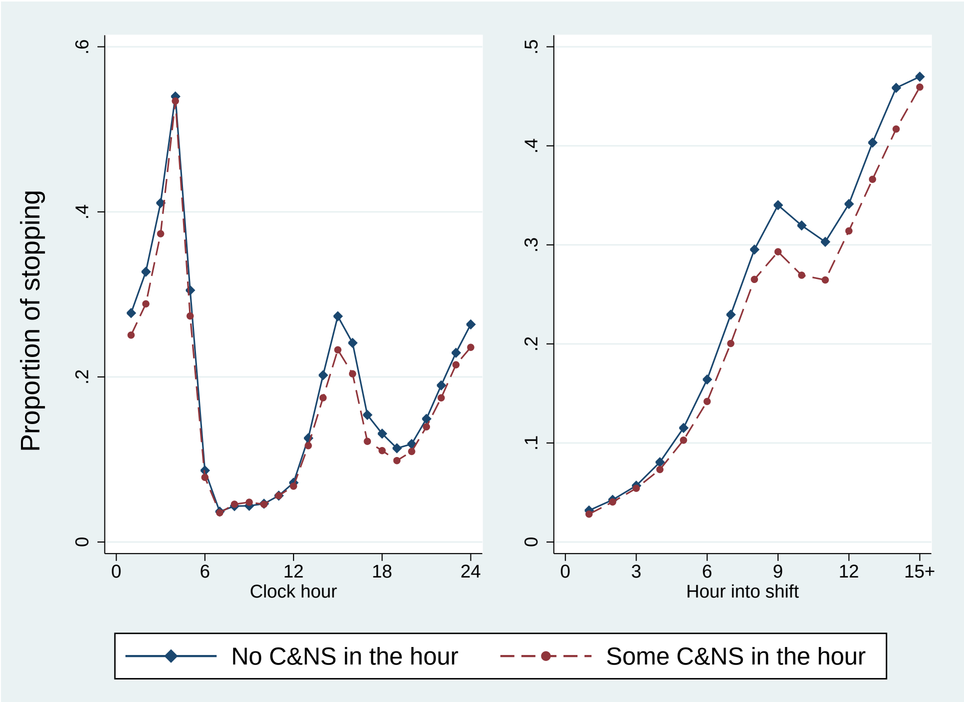
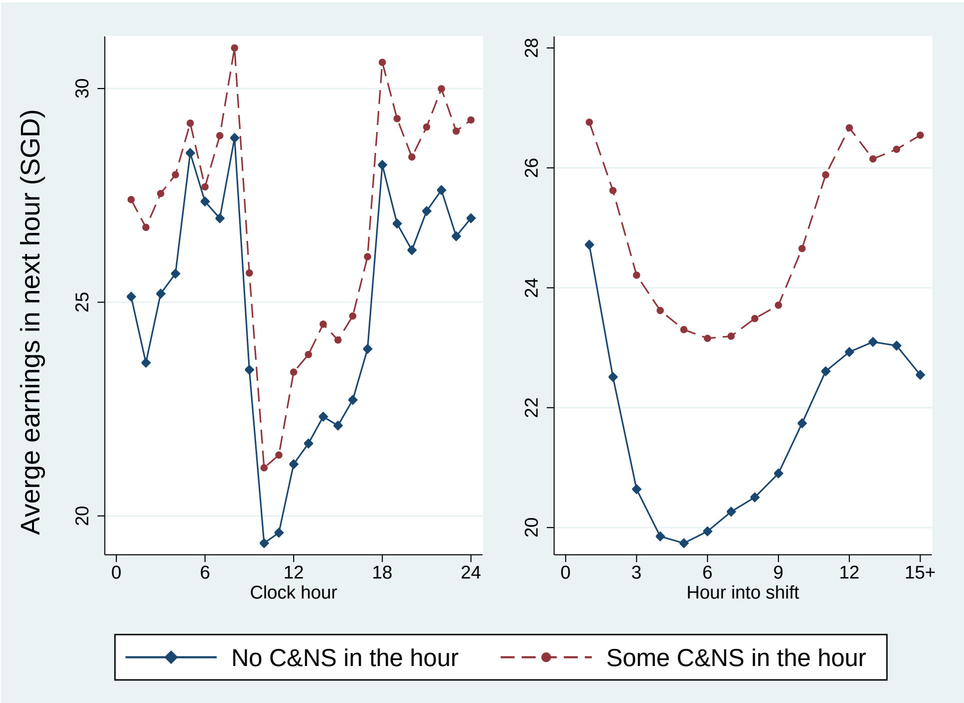


FIGURE 2. AVERAGE HOURLY EARNINGS IN NEXT: WITH AND WITHOUT C&NS



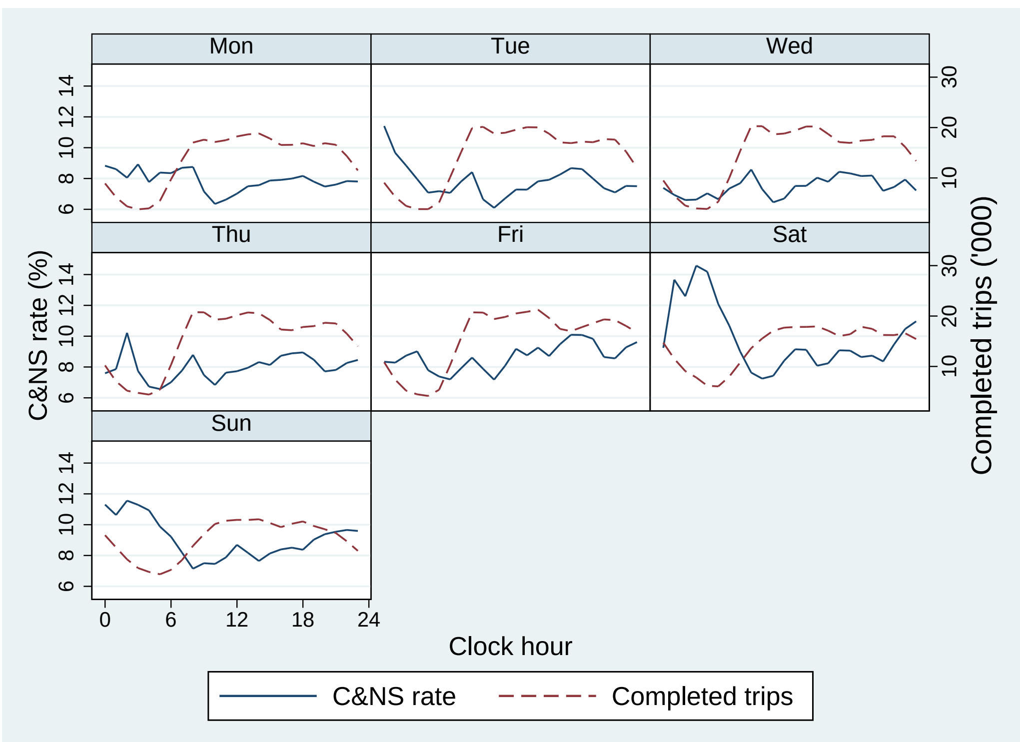
APPENDIX A Data cleaning

The data cleaning process includes the following steps

- failed bookings (bookings for which the system failed to assign a taxi; 2.65% of total observations)
- cancellations before confirmation (bookings that were cancelled before the system could assign a taxi; 2.00%)
- observations with missing vehicle information (30 observations)
- observations with start date before December 1, 2016 or end time before start time (0.01%)
- observations with trip duration shorter than 1 minutes or longer than 2 hours (0.25%)
- observations with trip fare of value less than 3.2 SGD or more than 100 SGD (0.13%)
- observations with trip distance shorter than 100 m or longer than 100 km (1.19%)
- observations in a shift with shift duration less than 1 hour or more than 24 hours (1.82%)
- observations in a shift with shift earnings less than 10 SGD or more than 1,000 SGD (0.01%)
- duplicate trips/bookings, i.e., trips/bookings with the same start time and driver (0.3%)

APPENDIX B Number of taxi trips and C&NS rate by hour and day of week

FIGURE A1. AVERAGE NUMBER OF COMPLETED TRIPS AND RATE OF C&NS BY HOUR AND DAY OF WEEK



APPENDIX C Proofs

Proof of Proposition 1

The net utility of continuing work

$$\Delta = V^{work} - V^{stop} = \begin{cases} (1+\lambda\eta)a_2 - c_2 + \varepsilon_2 & \text{if } u < t - a_1 - a_2 \\ (1+\eta)a_2 - (\lambda-1)\eta(a_1+u-t) - c_2 + \varepsilon_2 & \text{if } t - a_1 \leq u < t - a_1 \\ (1+\eta)a_2 - c_2 + \varepsilon_2 & \text{if } u \geq t - a_1 \end{cases}$$

$$P(stop) = P(\Delta < 0) = P\left(\varepsilon_2 < \begin{cases} c_2 - (1+\lambda\eta)a_2 & \text{if } u < t - a_1 - a_2 \\ c_2 - (1+\eta)a_2 + (\lambda-1)\eta(a_1+u-t) & \text{if } t - a_1 \leq u < t - a_1 \\ c_2 - (1+\eta)a_2 & \text{if } u \geq t - a_1 \end{cases} \right)$$

which is increasing in u. QED.

Proof of Proposition 1

Let $d^*(u) = 0$ if the driver stop when unanticipated earnings is u and $d^*(u) = 1$ when he/she continues. The expected earnings under d^* and parameter sets (a_1, a_2, c_1, c_2) are $t^* = E[a_1 + a_2 d^*(u) + u]$. The expected earnings under d^* and parameter sets $(a_1 + \delta, a_2, c_1, c_2)$ are $t' = E[a_1 + \delta + a_2 d^*(u) + u] = \delta + E[a_1 + a_2 d^*(u) + u] = t^* + \delta$. Thus, $t^* + \delta$ is equal to the expected earnings under the decision d^* and parameter set $(a_1 + \delta, a_2, c_1, c_2)$.

Under the target t^* and parameter set (a_1, a_2, c_1, c_2), if the unanticipated earnings are u, net utility of working is $\Delta(u|a_1, a_2, c_1, c_2, t^*) = a_2 - c_2 + l(a_1 + a_2 + u - t^*) - l(a_1 + u - t^*) + \varepsilon_2$. Under the target $t^* + \delta$ and parameter set $(a_1 + \delta, a_2, c_1, c_2)$, net utility of working is $\Delta(u|a_1 + \delta, a_2, c_1, c_2, t^* + \delta) = a_2 - c_2 + l(a_1 + \delta + a_2 + u - (t^* + \delta)) - l(a_1 + \delta + u - (t^* + \delta)) + \varepsilon_2 = a_2 - c_2 + l(a_1 + a_2 + u - t^*) - l(a_1 + u - t^*) + \varepsilon_2$, which is the same as $\Delta(u|a_1 + \delta, a_2, c_1, c_2, t^* + \delta)$. Thus, if d^* is optimal for $\Delta(u|a_1, a_2, c_1, c_2, t^*)$, it must also be optimal for $\Delta(u|a_1 + \delta, a_2, c_1, c_2, t^* + \delta)$.

Proof of Proposition 3

The marginal cost of spending effort in the second period is $MC = \partial c(e_1, e_2)/\partial e_2 = c_2(e_1, e_2)$. The marginal benefit of spending effort in the second period is η if $e_1 + e_2 + u > t$, and $\lambda\eta$ if $e_1 + e_2 + u < t$. Let e_2^l and e_2^h be the effort level such that $c_2(e_1, e_2^l) = \eta$ and $c_2(e_1, e_2^h) = \lambda\eta$. Since $c(e_1, e_2)$ is convex in e_2, $c_2(e_1,e_2)$ is increasing in e_2 and $e_2^h > e_2^l$. The optimal level of effort in the second period is :

$$e_2^* = \begin{cases} e_1^l & \text{if } t - e_1 - u < e_2^l \\ t - e_1 - u & \text{if } e_2^l \leq t - e_1 - u < e_2^h \\ e_2^h & \text{if } t - e_1 - u \geq e_2^h \end{cases}$$

which is decreasing in u

Proof of Proposition 4

OLS of y on i is

$$(i'i)^{-1}(i'y) = \frac{i'y/N}{i'i/N} \to \frac{Cov(i,y)}{V(i)} = \frac{Cov(u+a, \beta u + \varepsilon)}{V(u+a)} = \beta \frac{V(u)}{V(u)+V(a)}$$

OLS of y on x is

$$(x'x)^{-1}(x'y) = \frac{x'y/N}{x'x/N} \to \frac{Cov(x,y)}{V(x)} = \frac{Cov(x, \beta(\gamma x + \omega) + \varepsilon)}{V(x)} = \beta\gamma$$

OLS of y on x and i is

$$\left(\begin{bmatrix} x \\ i \end{bmatrix}' \begin{bmatrix} x \\ i \end{bmatrix} \right)^{-1} \begin{bmatrix} x \\ i \end{bmatrix}' y = \left(\begin{bmatrix} x'x & x'i \\ i'x & i'i \end{bmatrix} \right)^{-1} \begin{bmatrix} x'y \\ i'y \end{bmatrix} = \frac{1}{(x'x)(i'i) - (x'i)^2)} \begin{bmatrix} (i'i)(x'y) - (x'i)(i'y) \\ (x'x)(i'y) - (i'x)(x'y) \end{bmatrix}$$

The first element converges to

$$\frac{V(i)Cov(x,y) - Cov(x,i)Cov(i,y)}{V(x)V(i) - Cov(x,i)^2} = \beta\gamma \frac{V(a)}{V(a)+V(\omega)}$$

The second element converges to

$$\frac{V(x)Cov(i,y) - Cov(x,i)Cov(x,y)}{V(x)V(i) - Cov(x,i)^2} = \beta \frac{V(\omega)}{V(a)+V(\omega)}$$

APPENDIX D Effects of C&NS on the remaining working time and the remaining idle percentage

TABLE A1.—REMAINING WORK TIME (MINS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cancellation (dummy)	11.66***	4.04***	4.40***	4.70***	4.21***	4.61***	3.62***	4.24***
	(0.26)	(0.26)	(0.26)	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)
No-show (dummy)	9.17***	3.93***	4.26***	4.70***	4.18***	4.63***	4.13***	5.93***
	(0.42)	(0.39)	(0.40)	(0.40)	(0.40)	(0.40)	(0.41)	(0.42)
Cumulative hours	-36.96***	-26.33***	-26.33***	-26.28***	-25.91***	-26.24***	-26.16***	-25.77***
	(0.17)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.21)
Cumulative income ('00 SGD)	-37.79***	-44.88***	-44.78***	-44.70***	-53.54***	-44.68***	-44.66***	-53.61***
	(0.60)	(0.58)	(0.58)	(0.58)	(0.63)	(0.58)	(0.58)	(0.63)
Demand density	4.59***	3.12***	6.12***	3.60***	3.11***	3.65***	3.63***	3.34***
	(0.18)	(0.11)	(0.35)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
Previous bookings (count)					4.29***			4.39***
					(0.09)			(0.09)
Vehicles within 500m ('000)						-8.89***		-4.40***
						(1.18)		(1.19)
Distance to pickup (km)							-0.14	-0.80***
							(0.17)	(0.18)
Oncall duration (mins)							0.21***	-0.37***
							(0.03)	(0.03)
Driver FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour×day of week FE	-	Yes	Yes	-	-	-	-	-
Postal code FE	-	-	Yes	-	-	-	-	-
Hour×day of week×Zone FE	-	-	-	Yes	Yes	Yes	Yes	Yes
date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,108,572	31,108,572	28,087,962	28,069,984	28,069,984	27,757,937	27,683,044	27,375,698
R^2	0.601	0.636	0.638	0.638	0.638	0.637	0.639	0.639

Each column is a separate regression. An observation is a trip or a booking. The dependent variable for all columns is the remaining work time in minutes, i.e., the number of minutes from the end of the trip/booking to the end of the respective shift. Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE A2.—IDLE PERCENTAGE AFTER A TRIP/BOOKING (%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cancellation (dummy)	-1.515***	-1.161***	-1.218***	-0.894***	-0.897***	-0.746***	-0.772***	-0.724***
	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)	(0.023)
No-show (dummy)	-0.704***	-0.225***	-0.313***	0.052*	0.049*	0.200***	0.312***	0.334***
	(0.036)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)	(0.036)
Cumulative hours	-1.616***	-1.209***	-1.185***	-1.177***	-1.176***	-1.182***	-1.156***	-1.158***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Cumulative income ('00 SGD)	5.812***	4.329***	4.234***	4.208***	4.168***	4.215***	4.091***	4.054***
	(0.049)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.045)	(0.045)
Demand density	-2.315***	-1.677***	-3.760***	-1.537***	-1.540***	-1.569***	-1.545***	-1.591***
	(0.016)	(0.012)	(0.029)	(0.018)	(0.018)	(0.019)	(0.018)	(0.019)
Previous bookings (count)					0.018**			0.018**
					(0.008)			(0.008)
Vehicles within 500m ('000)						9.606***		9.337***
						(0.098)		(0.099)
Distance to pickup (km)							-0.328***	-0.225***
							(0.015)	(0.014)
On-call duration (mins)							-0.051***	-0.030***
							(0.003)	(0.003)
Driver FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	-	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour×day of week FE	-	Yes	Yes	-	-	-	-	-
Postal code FE	-	-	Yes	-	-	-	-	-
Hour×day of week×Zone FE	-	-	-	Yes	Yes	Yes	Yes	Yes
Observations	26,511,775	26,511,775	23,821,515	23,808,266	23,808,266	23,543,680	23,469,766	23,209,593
R^2	0.320	0.365	0.372	0.373	0.373	0.373	0.374	0.374

Each column is a separate regression. An observation is a trip or a booking. The dependent variable for all columns is the remaining idle percentage, i.e., percentage of time a driver is with a passenger during the remaining time (i.e., from the end of the trip/booking to the end of the shift). Standard errors clustered by drivers in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

APPENDIX E Instrumental-variables regression

Due to the fact that customers pay no penalties for C&NS, one of the common reasons for C&NS is passengers hailing a random taxicab that happens to pass by while waiting for the booked driver to arrive. Since the drivers do not coordinate with each other, the chance of a passenger seeing a random free taxicab can be considered as exogenous to the the booked driver' labor decisions. As a result, we can use the number of nearby free taxi vehicles around the time of booking as a valid instrumental variable (IV) for the occurrence of C&NS. Specifically, we will use the number of free taxi vehicles within 3 minutes after booking, within 100-m radius and within 200-m radius from the pickup location as the IVs. We control for postal code by hour-of-day by day-of-week fixed effects as well as the number of vehicles within 500 m and 1 km to absorb the spatiotemporal distribution of taxi supply over the city. Thus, the variation of C&NS that we use here is the change in C&NS due to free taxicabs moving around locally, keeping the broader market supply at 500 m and 1 km radius constant.

Table A3 reports the results. Since the difference in magnitude of the cancellation effect and the no-show effect on the hazard rate of stopping is small, and to increase the power of the IV estimates, we create a common dummy variable for C&NS. We also limit our sample to bookings, because the construction of free vehicle count at booking time is not well defined for street hail trips. Column (1) reports the OLS estimates using this new independent variable, and the estimated effect, at -0.199 (s.e. 0.0003) is similar to previous results. Columns (2) and (3) report the first-stage and second-stage estimates of the IV regression. Column (2) shows that the number of free vehicles within 100-m and 200-m radius from the pickup location increases the chance of C&NS, consistent with the story that passengers cancel and fail to show up because of random free taxicab passing by. The estimates are significant at the 1% level, indicating strong relationship between the IVs and the independent variable. Column (3) shows that C&NS that are due to free taxicabs near the pickup location tend to decrease the hazard of stopping work for the booked driver by 3.8 ppts (s.e. 1.8). The IV estimate is larger in magnitude than the OLS estimate, but less precise. The exogeneity test, with p-value of 0.24, fails to reject the hypothesis that the independent variables are exogenous. The F-statistics of weak identification test is 888, strongly rejecting the hypothesis that the instrumental variables are weak.

TABLE A3.—HAZARD RATE OF STOPPING WORK: IV REGRESSION

	OLS	2SLS	
Dependent variable	Quit	C&NS	Quit
C&NS (dummy)	-0.0199***		-0.0389***
	(0.0003)		(0.0176)
Free vehicle within 100 m (count)		0.0028***	
		(0.0001)	
Free vehicle within 200 m (count)		0.0004***	
		(0.0001)	
Observations	6,103,669	6,103,669	6,103,669
R^2	0.283	0.277	
Weak-identification F-statistic			888
Exogeneity test χ^2-statistic			1.377
			[0.241]

An observation is a booking. All regressions include driver fixed effects, date fixed effects, hour×day-of-week×postal-code fixed effects, demand, free vehicle count within 500 m and 1 km radius from pickup location, and a cubic function of cumulative hours. Standard errors clustered by drivers in parentheses. p-value of exogeneity tests in square bracket. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.