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Abstract

Commuting imposes financial, time and emotional cost on the labor force, which increases the cost of supplying labor. Theory suggests a negative or no relation between travel and working time for two reasons: travel time is a cost to supplying labor and commuting frustrates the traveler decreasing productivity. We use a unique dataset that records *all* commuting trips by public transport (bus and train) over three months in 2013 to study if commuting time affects labor supply decisions in Singapore. We propose a new measure of commuting and working time based on administrative data, which sidesteps issues related to survey data. We document a causal positive relation between commute time and the labor supply decision within individuals. Specifically, we show that a one standard deviation increase in commute time increases working time by 2.6%, controlling for individual, location, and time fixed effects.

There are two sources of variation in the elasticity of work time to travel time: across individual and within individual (time variation). While part of the cross-sectional variation may be captured by survey data, the time-variation is completely unexplored. First, we find that the cross-sectional variation depends on whether one engages in a service or manufacturing type of job. This cross-sectional variation might be missed out in survey-based responses due to a different selection process, based say on the proportion of industries in the S&P500. Second, we find that there is very large within individual variation in the elasticity, not based on calendar effects, like day of the week or month.

We investigate several potential explanations for this result. We find that in professions where interaction with co-workers and with customers is necessary, i.e. service jobs, disruptions in travelling to work cause a backlog and increase the working hours beyond the original travel delay. These (travel delayed) individuals are not compensated for the time that they put in, in addition to the usual number of working hours. This means that there is a cost shift from employer to employee. Given the recent trend of moving from manufacturing to service-based economies, it is most likely the positive elasticity will increase and become a larger economic burden.

JEL classification: D1, J22, J24, M54

Keywords: Commute time, labor supply, elasticity, task juggling, trains, buses, big data.

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"*Time spent travelling* ***during*** *normal work hours is considered compensable work time. Time spent in home-to-work travel by an employee in an employer-provided vehicle, or in activities performed by an employee that are incidental to the use of the vehicle for commuting, generally is no "hours worked" and, therefore, does not have to be paid*."
– United States Department of Labor

1. Introduction

Time is likely to be the most expensive and important commodity for an individual, and it has become more expensive as wage rates and GDP/capita have increased. Thus, the opportunity cost of each unit of time not spent working has increased, while the hours in a day remain constant. An important question in economics is how do we value time? A rich literature has developed looking at one aspect of the value of time - time spent travelling. This large literature (see Zamparini and Reggiani (2007) and Hamermesh (2016)) finds that the value of time as a percentage of hourly earnings has increased by more than 50% in the last 50 years. In this study, we use travel data to answer an important economic question: what is the elasticity of working time to travel time? Answering this question might help in answering related questions of how much leisure or home production time is valued in comparison to working time.

While most governments and Ministries of Labor do not consider travel time part of working time, economists have assumed that economic agents do. Cogan (1981), and subsequently textbooks in labor economics (e.g. Ehrenberg and Smith, 2003), assume that the number of workhours is optimally chosen given the commuting distance, which implies that labor supply is optimally chosen per day. Theory suggests that individuals account for commuting time as part of their work time (e.g. Becker, 1965; Cogan, 1981) and large commuting times may even impede labor force participation (Cogan, 1981). In other words, as the commute time increases individuals will spend less time at work.

Empirically, it is hard to document the relation between commute time and labor supply, due to lack of reliable information on travel time.[1] So far, the literature on the allocation of time is based on survey data.[2] While the use of survey data is very valuable in conducting economic

[1] Cogan (1981) examines empirically the effect of labor costs on labor supply and concludes that increases in daily fixed costs of work (e.g. commute costs) will reduce labor supply, at least for the sample of 898 married women, who work some time in 1966, that he analyses.
[2] See Juster and Stafford (1991), Aguiar and Hurst (2007) and Aguiar, Hurst, and Karabarbounis (2012) for surveys of the literature. More recently, Bick, Brüggemann, and Fuchs- Schündeln (2016, 2017) construct survey based working hour data that are comparable across countries. Analysis and discussion of this data can be found in Bick and Fuchs- Schündeln (2017, 2018).

research, with the availability of administrative datasets and computing power, one can study these questions with better precision and document within person dynamic effects of the relation between commuting time and labor supply decisions.[3] This paper uses exactly such administrative data to investigate the sign and magnitude of the relation between commute and working time. However, we also supplement our analysis with travel-related survey data.

In recent years, individuals are spending more and more of their time commuting (to and from work). For example, in the UK the number of people spending more than two hours travelling to and from work every day has jumped by 72% to more than 3 million, from 2004 to 2014, and the average commute time has increased from 45 to 54 minutes in this time period. In the US, the mean one-way travel time to work has increased by 18% to 26 minutes in 2013, while it was less than 22 minutes in 1980 (US Census Bureau, 2011 and 2014). The increase in commute time implies that there has been a substantial increase in explicit (time and petrol) labor supply costs. While, there have been some changes by employers to have flexible working hours and ability to work from home, these have not reduced the overall cost of commuting.

In addition to the pure monetary costs of commuting (petrol and public transport prices) and opportunity cost of time spent commuting, there is psychological evidence, which shows that commuting time is causing stress, tiredness, “road rage”, and general unhappiness (Novaco and Gozales, 2009; Gallup-Healthways Well-Being Index 2009-2010; Kahneman et al., 2004). In particular, Kahneman, Krueger, Schkade, Schwarz and Stone (2004) document that commuting is the least satisfying activity of all type of daily activities, which generates feelings of impatience and fatigue. In their study, increased commuting time is associated with increased blood pressure and musculoskeletal problems, lower frustration tolerance, and higher levels of anxiety and hostility. Hence, increased commuting time not only increases the time and monetory cost of labor supply but also affects one’s productivity at work, which has implications for the productivity and profitability of firms. Overall, studying the relation between commute time and labor supply is a first order question both from an urban and labor productivity point of view.

[3] Both approaches have their strength and weaknesses. For instance, using survey data may have non-representative samples, selection bias, attrition rates, changing survey subjects, non-comparable samples across countries, and under/over estimation of work time (propensity to supply conventional numbers of work hours). Administrative data also has significant limitations. For instance, we do not get a comprehensive view of the individual’s decision to commute, and we cannot observe the exact location of the home and work location. Therefore, we see the use of these two datasets as complementary and not substitutes. Indeed, in this paper we use both survey and administrative data for our analysis.

In this paper, we use two different datasets from Singapore. The first is a travel-related panel survey dataset over three waves from 2004 to 2012. This is very detailed data on the modes of transportation, travel time, and individual characteristics similar to the US Time Use Survey. This data allows us to measure the travel time to work and non-work related activities based on types of jobs and individual characteristics. The second is a unique dataset of *all* 6 million electronic travel cards (EZ-Link card) in Singapore, from August to October 2013, which we use to study the relation between commute time and labor supply.[4] The EZ-Link cards provide us with a wealth of information to study this relation. For instance, the cards are distinct for adults, children, and pensioners, which allows us to accurately identify working adults. Additionally, the cards document the time and location of embarkation and disembarkation of the cardholder and the mode of transportation used (bus and/or train).[5] This allows us to measure the exact commute time of the passenger on public transport, as well as to determine the time at work. The exogenous variation in the duration of each ride, i.e. delay due to traffic congestion or MRT breakdowns, hence exogenous shock to travel time within individual, while traveling to work enables the causal study of the effect of travel time on working time. The bus (public transport) stop can be precisely linked to the postal code in an area, which is linked to information on the nature of the destination (residential area, industrial area, central business district), to the survey data on individual characteristics at the block level, and to weather stations for localized weather information at the block level.

The time at work is measured imprecisely, because we estimate the time spent at work by the use of the EZ-Link card, which can potentially be problematic in the cross-section. However, since we can follow the same individual over time, the imprecision is less of a concern, unless the imprecision is correlated with commute time within an individual.[6] On the other hand, our measure of commute time and working time reduces measurement issues related to non-representative sample, recall/reporting bias, changing survey subjects, attrition rates, as well as accounting for within individual effects.

[4] The population of Singapore is 5.5 million. There are more EZ-link cards than the population because tourists can also purchase these cards.

[5] While we do not have precise information on race, nationality, cultural background, family size, residence status, and occupation of the commuter, we can infer these from the location of residence. We discuss this further in the data and results section.

[6] In other words, does the imprecision of working time increase when the commute time increases? Specifically, we attribute all the time spent once an individual leaves the train or bus in the morning until he/she gets back on the same bus or train in the evening as working time. As long as an individual travels to the same home and work location throughout the sample, the mismeasurement is fixed within individual. In addition, there is a bus stop every 500 meters in Singapore. We discuss this issue in further detail in the robustness section.

First, we document the travel patterns and purpose of travel of the population in Singapore using survey data. 26% of travel is commuting to work in Singapore in 2012, is similar to the US and UK, which implies that commuting, takes a lot of an individual's time. On average, 65% of travel across income groups is done by public transport in 2012. More specifically 49% of individuals earning above median income and 70% of individual below median, travel by public transport. The large share of higher income individuals using public transport implies that using data from public transport (EZ-Link cards) covers the largest share of work commute in Singapore and overcomes issues related to selection bias, which beset survey studies. As in UK and US, commute times by car have increased by 24%, from 2004 to 2012, which is a substantial increase. One important finding from our survey data is that there is strong recollection bias across individuals who co-travel by non-public transport (car, motorbike, or van) to the same destination, i.e. they rarely recollect the same length of the commuting time.

Next we measure the relation between commuting time and labor supply. Is a trip itself the outcome or is the trip just another intermediate product into the outcome (i.e. work)? Is travel time considered as time at work? Does travel time affect time spent at work? If variations in travel time are compensated by the amount of time spent at work, then the current economic definition of market work activity is inappropriate. Many examples come to mind: an individual staying an extra hour at work to complete her task because of the late arrival at work due to traffic congestion; an employee with longer commute time spends the same amount of time at work as an employee that has a shorter commute time and is paid the same salary.

We use the EZ-Link card to measure travel time and work time. The EZ-Link card allows us to define an individual through an anonymized ID associated with a registered commuter. This facilitates the ranking of the travel destinations of each individual by frequency, which allows us to identify home and work locations. We identify the home location for each adult in two ways: a) we calculate the most frequented destination (start or end) per individual, and b) the starting point of the first travel of the day and the last destination at the end of the day. Home is defined as the station where a commuter starts for 25 or more days across the sample. We then identify the work location for adults in two ways: a) the second most frequented destination per individual, and/or b) the final destination of the first trip of the day and the beginning of the journey after a long break from travel time. Workplace is defined only when a commuter uses public transport for arriving and leaving the workplace on the same day with a minimum frequency of 25 days across the sample. The longest duration between travelling to and from the same location is classified as market time. The rest of the destinations are other activities.

As such we can separate time in four categories, at home (non-market time, time spend away from market work), at work (time spent at the workplace), travel time, and other (non-market, leisure time).

The average commute time from the EZ-Link data is 35% higher than the public transport time recorded from the survey data. Survey data appears to suffer from strong recollection bias and severely underestimates travel time, as also shown in the discrepancy between driver and passenger travel time recollection. We find that on average in working time increases with the increase of within-individual variation in travel time.[7] As the commute time on a given day increases by one standard deviation the work time increases by 2.6%, or 0.1 standard deviations.

The positive causal relation, within an individual, is counter intuitive and inconsistent with the theoretical literature. Our result is not explained by late or early arrival at work or by adverse weather conditions at the time of leaving work or home. However, there is considerable cross-sectional variation in this relation across different individual characteristics. For instance, a part of the population exhibits zero or even negative working time elasticity to travel time changes, controlling for individual fixed effects. Using detailed (zip code and block level) data on alighting stations as well as building classification information, we can classify work locations as manufacturing based. We find that individuals travelling to industrial manufacturing estates exhibit large and negative labor supply elasticity to travel time, while those travelling to the central business district (CBD) exhibit positive labor supply elasticity.

We propose three potential explanations for our findings: (i) working time may appear longer on days with travel delay because one takes a break after work; (ii) working time appears longer because one stays at work due to adverse weather at the workplace; (iii) longer travel time negatively affects firm productivity and forces individuals to work longer to complete the same tasks. We find evidence supporting the last explanation. By nature of service production (and to an extent consumption), it is paramount to coordinate with others in the workplace on the timing of the working activities. The presence or absence of peers alters the production process (which in turn will affect consumption, at least in the service industry) and leads to rescheduling or multitasking by oneself or the team, thus lower productivity (see Coviello et al. (2014), (2015)). Therefore, in professions where interaction with co-workers and with the

[7] We cannot estimate this relation using the survey data, as the survey does not provide any information on the time spent in the activity related to the travel.

customers is necessary, disruptions in travelling to work will cause a backlog and increase the working hours beyond the original travel delay.

We investigate this hypothesis in two ways. First we use the alighting station to categorize an individual as working in the manufacturing industry. In the manufacturing industry the relation between commute time and labor supply is negative, which implies that individuals internalize commute time as part of working time. In services jobs, which are mainly located in the CBD, this relation is large and positive, implying substantial amount of unpaid overtime and decrease in efficiency. Second, we use the cross-sectional variation in individual occupations from the HIT survey to explain the sign and size of the elasticity coefficient. Specifically, individuals in professions where there are interactions with the consumers or interactive workplace (e.g. clerks, craftsman, etc.) have a large and positive coefficient. Individuals in jobs with fixed outcomes (e.g. technician, cleaner, etc.) have negative coefficients. Thus, if there is a fixed number of appointments that need to be rescheduled and one arrives late to work, this causes a knock-on effect on other tasks that forces one to work longer until all tasks are accomplished.

This paper makes several important contributions to the existing literature. First, this is the first paper to use and to compare travel times across survey-based and administrative datasets. Both datasets have shortcomings, but using them together allows us to learn more about labor supply. Second, the use of the administrative dataset allows us to make causal inference about the role of commute time and labor supply within an individual. Past cross-sectional studies cannot investigate this issue because they cannot track the dynamics of an individual's commute and market time. Third, and very importantly, we show that there is a positive relation between travel time and labor supply, which is in contrast to current theoretical assumptions and predictions of a negative or non-existing relation. We propose a parsimonious explanation for this result.

Our work is related to the following two broad literatures. First, we contribute to the literature on urbanization and specifically commute time as measured using an administrative dataset. Household surveys provide a top-down view, but there is increasing concern about non-response rates either to the survey or to important individual questions, and about inaccurate responses influenced by imperfect recall and a tendency to overestimate use of time. It is particularly difficult to get informative responses from wealthy households, and some other surveys oversample this group. This study unlocks the use of administrative data in the context of the use of time, which overcomes issues related to distrust and scepticism of survey data. Specifically, the survey data shows that individuals on very high incomes still take public transport in Singapore on a regular basis. For example, more than fifty percent of the population with above average income use some form of public transport daily. Furthermore, from the administrative data we find there is no negative selection into commuting to work based on weather, maximum travel distance, private vehicle availability, and day of the week.

Second we contribute to the literature on labor productivity. In many studies, the relation between working and travel time is either assumed or studied as an association, with little focus on identification. This is due to the nature of survey data, which does not allow for the study of exogenous shocks. In order to understand the relation between travel and working time, one needs to be able to disentangle the within commuter fixed effects from the causal relation between travel and work. For example, people that live closer to the work place might be poorer and therefore work the longest hours. As a result, one needs to use/exploit within individual variations. When using individual fixed effects, we find that shocks to individual travel time lead to longer working time, which contradicts traditional assumptions.

The rest of the paper proceeds as follows. In the next section, we provide some basic information on Singapore and the transport system in Singapore. Section 3 presents the data used in the paper and section 4 presents the results and robustness analysis. Section 5 concludes.

2. Singapore Setting and Background

Singapore is a small and densely populated South-East Asian city-state with a total population of 5.5 million people. It consists of the main island of Singapore and 63 offshore islands. The main island has a land area of 648 km^2, 42 km long and 23 km wide, see Figure 1. The Land Transport Authority (LTA), a statutory board under the Ministry of Transport, actively improves Singapore's integrated transportation policy to balance the growth in transport demand and the effectiveness and efficiency of the land transport system, due to limited space. Singapore is the first country in the world to have introduced various new urban development plans, notably the area license scheme in 1975 and the vehicle quota system in 1990, to overcome the space constraint. With the vehicle quota system and the highest cost of owning a car in the world, Singapore has a well-planned, efficient, and world-class land transport system that is well-integrated with the urban development of the country to ensure affordable public transport for the general population. CNN (2013) and urban rail community (World Metrorail

Congress, 2010) report that Singapore has one of the best and most advanced public transport systems in the world.

The main public transport services in Singapore include the bus, Mass Rapid Transit (MRT), Light Rail Transit (LRT), and taxi. Over the years, continuous efforts have been made to improve public transport quality and to keep it affordable, to make it an attractive alternative to the private car. The train and bus frequency during peak hours (7-9am) is 2-3 minutes and 5-7 minutes at other times. CNBC (2013) reports that Singapore is one of the most expensive places in the world to own a private car. It costs about US$85,000 to own a Toyota Corolla compared to US$16,000 and US$20,000 in the U.S. and in the U.K. Because of the high cost of owning private cars and the comprehensive public transport network, the majority of the Singaporean work force (affluent or poor) commute to work using public transport, as also captured in the Household Interviews for Travel Survey, discussed in Section 2.2.

Figure 1 presents the map of all public transport stations (MRT, LRT and bus stations) in Singapore. LTA reports that there is an MRT station within 8 minute walk and a bus stop every 500 meters in Singapore. Apart from the natural reserve (green segment of the map), all commercial and residential areas of Singapore are well supported by public transport. LTA (2013) reports that 63% of the total trips made in Singapore during peak hours are on public transport. There were about 7.4 million public transport daily passenger-trips in 2013.

Singapore introduced automatic contactless stored value smart cards (known as EZ-Link cards) for public transport in 2002. One can use the EZ-Link card for payment of all modes of public transport, regardless of operator as well as for parking and road toll payments. 96% of all commuting payment in Singapore is carried out through EZ-Link card payment (Prakasam, 2008).

The implementation of a uniform smart card system allows the introduction of a distance-based fare scheme for all modes of public transport in Singapore. The fare charge for each customer is based on the exact distance travelled, transport mode, and demographic attributes (there are lower rates for children, students, and senior citizens).[8] Customers have to tap their EZ-Link card on the reading device every time they enter and leave a train station or a bus. Thus, besides the information on boarding time and location, the data collected from EZ-Link cards

[8] Senior citizens and students pay 75% and 50% of the regular adult fare, respectively, and a flat fee beyond 7.2km.

contains detailed records of alighting times and destination location. These attributes allow for a detailed assessment of travel behavior and mobility patterns of commuters.

Commuters tend to continuously use one single EZ-Link card, with a unique card ID, for all their public transport journeys for substantial periods of time for two reasons. First, there is a high cost of purchasing a new EZ-Link card because of the associated technology. Second, EZ-Link cards are easily rechargeable and can be automatically recharged via electronic direct debit. Each unique card ID represents only one individual, because the system does not allow for more than one person to travel on a single EZ-Link card. This enables for highly disaggregated analysis of individual itineraries and opens new ways for understanding people's travel behaviour and choice.

2.1 Social Demographics of Singapore

According to the Singapore Bureau of Statistics, Singapore's resident population is 3.9 million with about 3.4 million Singapore citizens and 0.5 million permanent residents. There is about 1.6 million non-residents, resulting in a total population of 5.5 million. The median age of the resident population is 39.6 years. About 11.8% of the resident population are aged 65 years and over. Chinese constitute 74.3% of the resident population, while Malays constitute 13.3% and Indians 9.1%.

Over 81% (or 3.16 million) of the resident population live in Housing Development Board flats and 56.6% is concentrated in ten planning areas. Figure 2 shows that there are four planning areas with more than 250,000 residents, namely Bedok, Jurong West, Tampines and Woodlands, with Bedok leading with 289,750 residents. The five planning areas with the highest proportion of residents aged 65 years and over are Sungei Kadut, Outram, Downtown Core, Rochor and Bukit Merah. Newer estates have a higher proportion of younger working adults.

The Ministry of Manpower (MOM) reports that the average number of working hours excluding overtime is 46.2 hours per week in 2013, according to MOM survey. Table A1 reports the working hours across different industries. Individuals working in manufacturing and construction have the highest number of working hours of up to 53 hours a week, while individuals in the financial and insurance industry work on average of 41 hours.

2.2 Household Interviews for Travel (HIT) Survey

The first dataset we use is the Household Interviews for Travel Survey, which collects activity and mobility data for a typical weekday for an individual. A local subcontractor conducts face-to-face interviews of participants. HIT interviewees are required to provide at least 14 days of collected data, of which at least 5 have to be validated in order to receive a monetary incentive. More importantly, interviewees provide household and individual information (such as: postal code, X-Y coordinates of dwelling building, dwelling type, ethnicity, family size, age, citizenship, residency type, employment status, occupation type and industry, and personal income) as well as their means of transport, time, length and purpose of travel, but not the time spent at the purpose destination. The survey is reported at the individual-block level across Singapore. The individuals interviewed are randomly selected to be fully representative of the population mix in each block.

Below, we present the preliminary statistics of the social demographics of Singapore based on the 2012 HIT survey. We will use these area characteristics later in the analysis to explore the cross-sectional differences in the labor elasticity to commute time. Tables A2-A4 in the Appendix report the racial, occupation and citizenship distribution across different planning areas.

Table A2 shows the racial distribution of Chinese, Indians, Malay and other ethnic groups by planned area in Singapore. For each township, we calculate the proportion of respondents from a particular race out of the total number of survey respondents in the township. Figure 2 provides a map of the townships in Singapore. The townships with the highest Chinese population (over 90%) are Bukit Timah and Singapore River. Geylang and Woodlands are towns with the highest Malay population (over 20%). Geylang has traditionally been where most Malays reside for cultural and historical reasons and Woodlands is located near to Malaysia. Other, which is mainly white-collar expats, are mostly based in Newton, Downtown, River Valley and Tanglin. The variations in ethnic composition across different township allow us to identify the effect of cultural differences on the work-travel relation.

Table A3 shows the occupation distribution and variations across townships. The survey categorizes respondents into 10 groups: 1) Legislator, senior official & manager, 2) Professional, 3) Associate professional & technician, 4) Clerical worker, 5) Service & sales worker, 6) Agriculture & fishery worker, 7) Production craftsman & related worker, 8) Plant & machine operator & assembler, 9) Cleaner, laborer & related worker, and 10) Armed forces personnel. This breakdown allows us to relate the type of individuals that substitute travel and working time. The majority of Singaporeans classify themselves as either professionals or service and sales workers. Newton, River Valley, Singapore River and Tanglin have the largest percentage of residents working as professionals. These townships on average have more white-collar expats with some of the highest income.

Table A4 shows the distribution of different types of citizenships across Singapore. The survey distinguishes between Singaporean citizens, permanent residents, and others. Others are then categorized in 7 groups: Employment Pass (highly skilled migrants), S Pass (mid-level skilled staff earning more than $2,200 a month), Work Permit (low-skilled necessity based from approved source country in determined employment areas), Work Permit (Foreign Domestic Workers), Dependent's Pass, Long Term Visit Pass, and Student Pass. There is large cross-sectional variation in citizenship. The highest proportion of Singaporean citizens is in Bishan, Hougang, Rochor and Toa Payoh, the first urbanized areas of the country. In contrast, the highest proportion of employment pass workers is in Downtown, River Valley, Singapore River and Tanglin, mostly white collar expat workers. This result is corroborated by the finding that some of the highest proportions of dependent passes and foreign domestic workers are found in these areas as well. More importantly, the substantial variations in ethnicity, occupation and citizenship allow us to understand how different cultural and labor characteristics are related to the elasticity of market time to travel time.

3. Data and Preliminary results

3.1 Survey Data

We start our analysis with the HIT survey data related to travel destinations and travel times. Table 1 provides the distribution of the purpose of travel of survey participants. Most travel, 26%, is related to commuting (i.e. travel to go to work) in Singapore in 2012, which is similar to the US and UK. The proportion of travel time spent on commuting to work has increased by 3% from 2008.

Table 2 presents the use of different modes of transport between 2008 and 2012 for the working population across different income groups.[9] 65% of all travel is done by public transport, up from 58% in 2008, while 21% is done by car or taxi, down from 27% in 2008.

[9] The inference does not change if one uses the whole survey population. 62.6% of the population used public transport in 2012 (60% bus and the rest MRT and LRT) and 54% in 2004 (66% bus and the rest MRT and LRT).

More than 60% of individuals earning less than 7,000 SGD used public transport in 2012, which represents over 80% of the Singaporean population. Use of public transport is also popular among the top income earners, with more than 37% using public transport in 2012 up from 21% in 2008. This distribution implies that public transport and EZ-Link cards are used by the whole cross-section of society to a large extent, and public transport data provides a good coverage of the working population.

Table 3 shows that commute time by car has increased steadily from 21 minutes in 2004 to 26 minutes in 2012, a 24% increase. The commute time of all other means of private transport: motorcycle, van, shuttle bus, and taxi, has also increased substantially from 2004 to 2012. The only exception is public transport, where the commute times by bus, MRT and LRT, have either remained the same or just slightly increased from 2004 to 2012. This is not surprising as the Singapore government has steadily increased the resources invested in public transport and has increased the number of MRT stations by introducing two new lines in 2009 and 2014 covering an extra 56 kilometers of rail (the whole length of the country).

More importantly, Table 3 shows that the reported travel time of passengers in cars, vans and motorcycles is consistently lower than that of the drivers of the vehicle, by a minimum of 8% and a maximum of 40%. This result is quite surprising as the two commuters (driver and passenger) are from the same household and depart from the same location at the same time. In order to control for other heterogeneous effects, i.e. the result being driven by individual characteristics, we investigate the bias across different household characteristics in Table A5. The results show that the recollection bias is large, positive, and highly statistically significant for almost all subgroups, with very few exceptions in categories with few observations. This implies that there is considerable recollection bias or different perception of time spent on the road depending on whether one is actively involved in driving or not.

3.2 EZ-Link Card Sample

Our sample data provides all the travel by public transport at the individual level, in Singapore with *individual card ID*, for the period August-October 2013. The individual card ID facilitates the tracking of the traveling, working and leisure patterns of every individual at all times across our sample period, as long as they commute by public transport. The data provides individual characteristics of the commuters, because each EZ-link card also serves as a supplementary identification and concession card for students of recognized educational institutes and citizens above sixty years old.[10] LTA classifies the *passenger types* into: adults, children/students and senior citizens. This classification allows us to more accurately identify the commuting working adults.

The data also reports 1) the *mode of transport* (bus, LRT and MRT), 2) the *service number* of the transport (bus, LRT and MRT service number and vehicle registration number), 3) the *boarding and alighting station numbers*, and 4) the *ride start and end date, time and distance* of every ride for all commuters. All bus stops in Singapore have a B+5 digit code. The first four digits of the bus stop code identify the location of the bus stop. The last digit is used to differentiate the direction of the service. If the bus stop code ends with '1' for a service traveling from location A to B, the pairing of this bus stop across the street will have a bus stop code ending with '9'.

This information allows us to track the location and commute of every individual across time. It facilitates a very accurate measurement of travel time and the likely location of an individual's home and workplace. For example, the most frequent stop, the first boarding and last alighting stop of the day is most likely to be the home stop of an individual. It also allows one to accurately identify the work place of a full-time working adult that commutes by public transport to the same work location and back home every day. The duration of each ride allows us to study the delay, due to traffic congestion or MRT breakdowns, hence exogenous shock to travel time within individual, while traveling to work.

The data includes all the rides that an individual makes during the day organized by *ride ID*. The data also aggregates these rides into a journey with any combination of bus, LRT and MRT with a *journey ID*. The journey ID is part of the Distance Fare scheme for a more integrated fare structure, which ensures that commuters can make transfers (from bus to MRT/LRT and vice versa) without incurring additional costs. A single journey includes up to five transfers with a maximum of 45 minutes per transfer. One can take up to two hours to complete a journey, with a limitation that one's current public transport service number must not be the same number as the preceding service number. One can only enter and exit the MRT/LRT network once in a journey. Otherwise, it is considered a new journey for a commuter, which is more costly. This information is important in measuring a commuter's

[10] Students and senior citizens are carefully checked for status during the issue and purchase of the EZ-Link card. There are regular conductors and ticket inspectors at all MRT stations and bus routes to ensure against misuse of concession cards. Any offender is subject to jail terms or fines of $540 or $750 SGD. Media, Netizens, and newspapers often publicly shame perpetrators, so that they do not regress to committing the offence again.

travel time to work without being affected by the number of required transfers to their destinations.

We supplement the travel data with Geographic Information Systems (GIS) data, which includes all postal codes in Singapore. Since 1995, a postal code in Singapore consists of 6 digits. The first two digits are the sector code and the last four digits represent a delivery point within the sector, which allows one to accurately pinpoint living and working locations. For example: Block 335 Smith Street with the postal code 050335 means the building is located in sector 05, as classified by the Urban Authority of Singapore, and the last digit 335 represents the block number 335.

Public and private residential, commercial and industrial buildings are assigned different postal codes in Singapore. Thus, we have information on whether a bus, LRT or MRT stop is located near a residential, commercial or industrial building. We use this information to create a dummy variable equal to one if the work stop is located near an industrial building and zero otherwise. This dummy variable allows us to differentiate between manufacturing and service jobs. To proxy for the cultural and labor characteristics of individual commuters, we match every bus stop/LRT/MRT (hereby bus stop) to a postal code in the HIT data. The furthest distance of a bus stop from a HIT block is 2 kilometers while the shortest distance is 10 meters.[11] Finally, we use weather station data to gather information on heavy rain mornings and afternoons. Singapore has 66 weather stations (manned and automatic) scattered across the country, which provide and disseminate information at 30 minute intervals. We use the XY co-ordinates of the boarding bus stop to determine the closest weather station and collect information on the weather conditions around the travel time of the individual from home in the morning and from work in the afternoon.

3.2 Measuring Travel and Market Time

To measure travel time to work and market time at work, we first identify the home location for each individual. We do this in two ways: a) we calculate the most frequented destination (start or end) per individual, and b) the starting point of the first travel of the day and the last destination at the end of the day. Home is defined as the station where a commuter starts for 25 or more days across the sample. We then identify the work location for adults. This is

[11] The distance between a bus stop and the HIT block is dictated by the population density of each area.

computed in two ways: a) the second most frequented destination per individual, and/or b) the final destination of the first trip of the day and the beginning of the journey after a long break from travel time. Workplace is defined only when a commuter uses public transport for arriving and leaving the workplace on the same day with a minimum frequency of 25 times across the sample. The rest of the destinations are other activities.[12]

With this classification, we define travel time to work as the duration of a journey from home station to workplace station in a day. We define market time as the duration between the time a commuter arrives to the work place station and the time the commuter boards a public transport from the workplace station or the opposite station.[13] This measure might overestimate working time, as individuals might not use all the time at work to carry out work, however the same issue arises with survey analysis. However, studies based on time-use surveys also do not account for the different activities, unrelated to the job, performed while being on the job. There is some data on such activities in the American Time Use Survey, but it has only recently been used by Burda, Genadek and Hamermesh (2016, 2017) to understand cross-sectional differences in activities carried out when not working at work.

By Singapore's labor law, a full-time worker is one that works at least 35 hours a week. We use only individuals for whom we can identify a home and a workplace and that travel at least 25 times during the sample period. This leads to a sample of over 652,000 travelers. We conduct robustness analysis for travelers that go to work for more than 30 days and 40 days over the sample period.

4. Results

4.1 Commuting and Market Time Statistics

Table 4 presents the basic statistics of individual trips for the whole population. There are about 517 million individual-trip observations in the sample, out of which 410 million are adults, 54 million are children and 52 million are senior citizens. 61.6% of the trips are done by bus and 38.4% by MRT/LRT. The proportion of bus trips is very close to that reported by the HIT survey in 2012, as reported in the previous section. Therefore, the survey data is representative

[12] We report results using the first way of classifying home and work locations, however the results remain quantitatively unchanged when using the second classification methods. Results are available from the authors upon request.
[13] The last digit of each bus station number is either 9 or 1. If it ends with '1' for a service traveling from location A to B, the pairing of this bus stop across the street will have a bus stop code ending with '9'.

of travel means used by the public, i.e. there is no bias in recollecting information on the mean of transport.

We classify work and home stations as described in section 3.2. We retain only adults that travel daily to and from a classified ‘work station’ for at least 25 days in the sample, for a sample of 29 million individual-trip observations. There are 652,936 working adults in our sample.

Table 5 shows that Singaporeans work on average 10 hours. For a five-day working week, we estimate that individuals in our sample work for 50 hours, which is slightly higher than the average working time reported by the Ministry of Manpower in Table A1 in the appendix. For comparison, in the US, the average employed adult works 8.46 hours including travel time to work, and men (8.95) work on average 1 hour more than women (7.86).

A working adult travels on average about 30 minutes to their work location, and the standard deviation of travel time is 17 minutes, about 57% of the travel time. Therefore, there is substantial cross-sectional and time-series variation in travel time despite the short travel distances in Singapore. The average commute time from the EZ-Link data is 35% higher than the average public transport time recorded from the survey data. Survey data appears to suffer from strong recollection bias and severely underestimates travel time for passengers, as also shown in the discrepancy between driver and passenger travel time recollection. Finally, we also report the average income based on merged EZ-Link and 2012 HIT data at the block level. The average income of the working adults in our data is 3,334 SGD a month, which is comparable to the average Singaporean income of 3,480 in 2012 as reported by the Ministry of Manpower. Therefore, the traveling sample is highly representative of the country’s working population.

One concern might be that there is no variation in working and travel time across different townships, as individuals optimize their housing and commute decisions. Table 6 shows the distribution of passengers in our sample across Singapore and the mean and median of market and travel time in different townships with more than 100 travelers. There is substantial cross-township variation both in market and travel time. The minimum average (median) market time among townships is 9.0 (9.7) hours and the maximum average is 11.2 (11.4) hours. The minimum occurs in Central Water and the maximum in Sungei Kadut.

4.2 Extensive Margin

The first step in our analysis is to understand when individuals chose to supply labor, extensive margin. There are several issues that affect how and when individuals go to work. The first is the effect of heavy rain in the morning, which might cause travel delays and disruption. On such days, individuals may choose to work from home (not go to work), they may choose to drive or take a taxi, which will show up as a non-working day in our sample. Second, individuals might work less than five days a week and work longer on days that they go to work.

Table 8 presents the results for the extensive margin analysis from fixed effects panel linear probability model. The dependent variable is equal to 1 when an individual goes to work during the working week as per our definition, and zero otherwise. To investigate the rain related absenteeism, we include several proxies for rain related impediments at the beginning of the day. We use hourly data from all weather stations in Singapore, between 7 and 9 AM. We then match each individual's boarding station to his/her closest weather station. We calculate the average and maximum rain duration and rain amount every morning. We include a dummy variable on whether individuals in the household own a car, to proxy for the substitution effect between car and public transport. This information comes from the HIT survey and is only available at the block level. We also control for other effects like travel distance, whether the mean of transport is a bus, and the average travel time. We use day of the week fixed effects to capture the choice of working from home on certain days or parental leave days, therefore exclude time fixed effects. Columns (1) and (2) show results with individual fixed effects, which are dropped in columns (3) and (4), when we introduce individual invariant effects like vehicle available and average travel time. Standard errors are double-clustered at the individual and travel day level, see Cameron, Gelbach and Miller (2011).

We find that neither the average nor the maximum rain amount in the morning affects the decision to work. Longer rain duration decreases the propensity to go to work, on the margin. However, the propensity to commute to work actually increases with the availability of a private car. This is probably because one can choose to be picked up by car if the rain persists throughout the day. It is worth noting that individuals that tend to commute for a longer time as well as individuals that commute by bus have a lower propensity to go to work.

We investigate the day of the week effect by including day of the week dummy variables in all our specifications, where the baseline day is Monday. The results show that there isn't that much of a difference in the propensity to go to work between the different days of the week and this effect holds regardless of the inclusion of individual fixed effects. Individuals appear to have a slightly lower propensity (6%) to work on Fridays. Overall, the results in Table 7 show that the choice of going to work mainly depends on the travel distance and on traveling by bus, rather than rain or day of the week.

4.3 Intensive Margin

Next we turn to the analysis of the relation between commuting time and working time, i.e. when one does go to work, how much to do they work, conditional on travel time. Economic theory suggests that individuals account for commuting time as part of their work time. As a result, individuals will spend less time at work if their commuting time increases. Thus, we form our null hypothesis as follows:

H1: Commuting time is negatively correlated to market time.

We test this hypothesis by regressing travel time on market time controlling for unobserved individual fixed effects, time fixed effects, time of travel, and weather. Table 6 reports different specifications of the panel regression of travel time on market time, with individual and time fixed effects. Column 1 of Table 7 shows the simple regression of travel time on market time with individual and time fixed effects. For every minute increase in travel time, an individual works an additional 44 seconds. The exogenous variation in the duration of each ride, i.e. delay due to traffic congestion or MRT breakdowns, hence exogenous shock to travel time within individual, while traveling to work allows us to interpret this coefficient as a causal one. The result is surprising and is contrary to the negative or insignificant relation suggested by economic theory, as one expects travel time to either be independent from or negatively correlated (substitute of) to market time. In other words, an individual should not work an additional 22 minutes over her 8 hour regular working time, just because she spends an additional 30 minutes over her average time travelling to work. This result suggests a paradox in the positive relation between commuting time and market time.

There can be a few mechanical explanations for the positive coefficient. Individuals who travel earlier or later in the day have shorter trips, because the roads are less congested. Alternatively, the commute time is more likely to be shorter during peak hours, because of the higher frequency of public transport during that time. “Start early” is a dummy variable indicating when an individual starts work 30 minutes before her average starting time. “Start late” is a dummy variable indicating when an individual starts work 30 minutes after her average starting time. "Peak Hour" is a dummy variable that indicates when a trip starts during peak hours (7-9 am). Travel*Start Early, Travel*Start Late and Travel*Peak Hour are interaction terms of travel time and the start of travel.

Results in Columns (2)-(4) show that individuals who start work early, work longer hours (quarter of an hour) than their average on the days they start work early. The impact of longer travel time on their working time is also larger. The interaction term between early start and travel time is positive and statistically significant. Individuals who start work late work substantially less than their average on days when they are late. However, a longer travel time for late starting individuals is not related to working time. Individuals that travel during peak hours also work on average longer (12 minutes) than those not travelling at peak hours. Travelling during peak hours has a slightly smaller positive relation to work time.

One potential explanation for our results is that days on which one travels longer are bad weather days. Large amounts of rainfall may lead to longer bus journeys or more people taking public transport. In addition, persistent rain might cause people to wait it out at the end of the working day rather than trying to get to the station in the rain, making it look like they are working longer. We create a heavy rain dummy variable for the starting station at the beginning and at the end of the working day. Here we exploit the information we have on the location of each individual across different times of the day, which we link to national weather service data for the nearest weather station. We use hourly data from all weather stations in Singapore. We classify a commute as affected by heavy rain "Heavy Rain" dummy equal to one, when there is 7mm of rain in an hour in the location of the commute (home or work) at the time of the commute. The U.S. Geological Survey in the U.S. Department of the Interior defines heavy rain as greater than 4 mm per hour, but less than 8 mm per hour. [14] We classify the destination of the commute as affected by heavy rain "Heavy at Alight" dummy equal to one, when there is 7mm of rain in an hour in the destination of the commute (home or work) at the time of alighting. Results in column (5) show that heavy rain seems to decrease working time on average, i.e. people leave work earlier when they expect heavy rain to occur. Also, heavy rain attenuates the effect of early and late start. Heavy rain does not seem to have any impact on the effect of travel time on working time.

[14] The average daily rainfall in June, July and August in Singapore is 6mm a day. 7mm of rain in an hour is the whole day's rainfall in one hour, therefore very large.

Finally, we control the previous day's working time. There is positive inertia in work, where if one worked long hours one day she will work long hours the next day.[15]

In summary, we find that market time is positively associated with travel time, contrary to what economic theory assumes. This paradox is not explained by whether an individual starts her work early for the day, peak hour effect, and the weather condition during the commute. Our findings have important implication for the common assumption in economics that travel time is of part market time and they are negatively correlated.

4.4 Time-series Variation of Delay

From the analysis in Table 8, there appears to be some time-series variation in the effect of travel time on working time, depending on how early or late an individual starts work. Individuals starting early seem to have some expediency of getting to work, while those that are delayed do not seem to worry much about their delay. We investigate this variation in effect further with two extra pieces of analysis. First, we try to break down the early and late start in different subcategories ranging from less than 15 minutes to more than one hour. Second, we investigate repeat delayed arrivals.

Table 9 presents the analysis for different early and late start time. In this regression we control for relevant variables from the previous analysis: lag dependent variable, peak hour, travel time*peak hour, industry dummy and travel time*industry dummy and include both time and individual fixed effects. We start the analysis with early arrivals, those that appear to have some expediency to get to work. Column (1) shows that there is considerable increase in the elasticity of work time to travel time, when an individual starts work less than 30 minutes early and more than 30 minutes early. The interaction term increases form 0.12 to 0.65, i.e. an individual that gets to work more than 30 minutes early increases working time by 1:49 minutes for each minute of travel delay. In column (2), we break down the less than 30 minutes early start into less than 15 minutes and between 15 and 30 minutes early. The result shows a hierarchy of increases in elasticity from 0.05 for 15 minutes early to 0.70 for more than 30 minutes early. Column (3) investigates the same coefficients, but for times when an individual starts work more than one hour early than their average time. An individual starting one hour earlier than usual, works 2 more minutes for every minute of travel delay. Finally, column (4) breaks down the pre- and post-30 minutes early start in <15, 15-30, 30-60 and >60 minute

[15] The results remain qualitatively similar when including only individual fixed effects, so that we allow for common shocks to public transport in a particular day. Results are available from the authors upon demand.

buckets. Column (4) shows a clearly increasing effect of travel time on working time, from 0.06 to 0.78, conditional on how early one starts work, or how expedient the work that needs to get done is.

Turning to the late arrivals to work, the picture changes depending on how late one arrives at work. Column (1) shows that when an individual arrives less than 30 minutes late, the travel time negatively affects working time, while this effect is large and positive for arrival more than 30 minutes late. In column (2), we break down the less than 30 minutes late start into less than 15 minutes and between 15 and 30 minutes late. While the elasticity for up to 15 minutes late remains negative, it already turns positive, 0.04, for those arriving between 15 and 30 minutes late. Column (4) breaks down both the pre and post 30 minutes late arrival and the same picture as before emerges. The later one arrives to work the more sensitive they become to delays in travel time.

Next, we turn to understanding the late arrival to work effect a bit better. It is slightly puzzling that individuals, who start work late, both work less and care less about being delayed by traffic. This may occur due to the fact that one already had little work to do, therefore decided to show up late to work. However, it may also be because most people only arrive to work late once and forgive themselves for the delay or catch up work at a different time. We investigate the effect of arriving to work more than 30 minutes late, even though they left home on time to arrive to work on time, i.e. the late start is due to travel time.

Table 10 shows the analysis for delays that occur at different frequencies within a month: once a month, two times a month, or three or more times a month. Column (1) shows that the elasticity of travel time on working time is positive and similar to the results in Table 8, 0.74. However, column (1) shows that the total effect of travel time on working time for those arriving late for the 1^{st} time is negative, -0.31, i.e. delay has a negative effect on travel time, which is congruent with current theory. However, the negative relation decreases with the number of delays, and is zero after three or more delays. In columns (2) and (3), we control for important variables from Table 8 and also for early and late working time. In both cases, the elasticity due to the number of delays decreases and it is still positive from the 1^{st} delay.

Overall the analysis in this section shows that there is considerable within individual time-series variation in elasticity of travel time to work time, ranging from negative to positive. This variation depends on how early or late one goes to work, on whether one unintentionally arrives late and how many times one arrives late to work. None of these effects depend on a particular day of the week or month, which means these effects can only be captured using complete panel data on individual work and travel times.

4.5 Cross-sectional Variation in Beta

The average effect of travel time on working time appears to be large and positive. This warrants further investigation of the cross-section variation of the coefficient. Figure 3 and Table 11 show the township variation in the estimated relation, beta. There appears to be a long right tail in this distribution. However, the average beta for only 2 out of 54 townships in our sample is not different from zero and for only 7 out of 54 (13%) is either zero or negative. Areas, where white-collar employees dominate, like River Valley and Rochor, exhibit either zero or large and negative coefficients. This implies that some part of the populations does not show a positive beta, but still the majority of the population shows a positive beta.

We repeat the same analysis at the individual level and extract individual regression beta coefficients. Figure 4, Panels A and B, depict the distribution of the individuals against the normal distribution. Panel A shows that there are some very large betas, both negative and positive. When we restrict the analysis to betas between -10 and +10 (dropping 17% of the sample), we can observe that there is a larger than normal part of the sample that exhibits a beta equal or close to zero. However, the distribution is right skewed. Overall there is a vast heterogeneity of commuting time elasticity of labor supply across individuals. The natural question is what explains this cross-sectional variation?

4.6 Causality

The results so far are based on identification arising from cross-sectional within variation in travel and working time, i.e. individual increase in travel time, which is unrelated to the characteristic of the traveller. However, before, we try to understand the magnitude of the coefficient of elasticity, we first show that our results are also causal using well-identified exogenous shocks to travel time. First, we show an instrumental variable (IV) regression, where we use weather as an exogenous shock to travel time. Second, we construct two placebo tests to rule out reverse causality.

It is hardly disputable that adverse weather conditions affect travel time. We use extreme weather conditions around the home area, in the hour before and after the start of travel to work, to identify exogenous changes to travel time. We match home locations to the weather stations in Singapore and calculate four instruments: (1) the amount of rain in the next hour after start of travel from home to work, (2) the amount of rain in the current hour of travel, (3) a heavy rain dummy in the current hour of travel, more than 7mm, and (4) a heavy rain dummy in the next hour after start of travel, more than 7mm.

Table 12 presents the results of the first stage effect of the instrument on travel time and the second stage regression. The first stage results show that the instrument is strong and relevant, with F-statistics of both the Sanderson and Windmeijer (2016) test and the Anderson and Rubin (1949) Wald test larger than 10, as recommended in Bound, Jager, and Baker (1995). The rainy day coefficient is negative and large, and travel time decreases under adverse weather conditions in Singapore. This might occur for two reasons: first, more buses and trains will be provided in heavy rain days by LTA in expectation of more people taking public transport. Second, less people will drive on those days and therefore ease the congestion for the bus rides. The second stage results confirm our prior findings of a large and positive relation between travel and working time.

To verify that our results are not by chance, we construct two placebo tests. First, we investigate the relation between lag travel time and today's working time. How much one works at time *t* should not affect the previous day's travel time, i.e. past travel time is independently (almost randomly) determined from current working time. Second, we investigate the relation between today's working time and yesterday's commute time. Yesterday's commute time ought not to affect how much an individual works currently.

We run a panel regression with individual fixed effects and double clustered standard errors. Results in Table 13 show that there is no relation between current today's working time and previous day's commute time. The result implies that the uncovered positive relation between commute and travel time only holds within individual within the same working day and is not a random finding driven by the large number of observations or exists by chance.

4.7 Explaining Findings

There are three potential plausible explanations for the positive coefficient. First, working time may appear longer on days with travel delay, because in frustration one takes a break after work. Second, working time appears longer because one stays at work due to adverse weather at the workplace. Third, longer travel time negatively affects productivity within a team or group of workers and forces individuals to work longer to complete the same tasks.

Kahneman, Krueger, Schkade, Schwarz and Stone (2004) document that commuting is the least satisfying activity of all type of daily activities, which generates feelings of impatience and fatigue. In their study, increased commuting time is associated with increased blood pressure and musculoskeletal problems, lower frustration tolerance, and higher levels of anxiety and hostility. Imagine one is trying to get to work early, because one has a lot of work to get through the day. However, one gets stuck in traffic, and arrives later than intended. Once everything is completed, one may decide to vent this frustration by just going for shopping or a drink after work, which may make it appear as working longer. This will result in going to a different location for a drink and returning home form a different station than the work public transport station. We identify all the times that an individual leaves work from a station that is not the 'work station'. We create a dummy variable 'Ch.Stat.' equal to 1 if the individual has changed station, and zero otherwise. We also construct a dummy variable 'Break' for instances when an individual not only changes station but also leaves work more than one hour later than the average leave time.[16]

Table 14 shows that, while starting early is positively related to changing stations, higher market time and higher travel time are both negatively related to changing stations. In addition, adding abnormal travel time as a control variable shows that abnormal travel time is negatively related to changing stations. Longer market times are related to a higher propensity to take a break after work, which is understandable. However, arriving early and longer travel time and longer abnormal travel times are negatively related to taking a break after work. Overall, it does not appear that the positive relation between work and travel time is related to a break from work making it look like one is working longer.

The second hypothesis is related to one appearing to work longer, because one stays at work longer on days it rains hard at the time to leave work. First, we classify a commute as affected by heavy rain "Heavy Rain" dummy equal to one, when there is 7mm of rain in an hour in the location of the commute (work) at the time of the commute from work to home. The results in columns (5)-(6) in Table 8 suggest heavy rain does not affect an individual's working time.

[16] The results are robust to using other late leaving times from work, i.e. 3 hours later and are available from the authors upon request.

The final explanation relates to the interaction between workers and customers. By nature of production (and to an extent consumption), it is paramount to coordinate with others in the workplace on the timing of the working activities. The presence or absence of peers alters the production process (which in turn will affect consumption, at least in the service industry) and leads to rescheduling or multitasking by oneself or the team, thus lower productivity (see Coviello et al. (2014), (2015)). Therefore, in professions where interaction with co-workers and with customers is necessary, disruptions in travelling to work will cause a backlog and increase the working hours beyond the original travel delay. This is not a reduction in productivity or efficiency of the individual, but rather a delay mechanism in the work process and efficiency of the unit. For example, if a hairdresser has an appointment at 8:30am and he arrives to work at 8:45am, either the customer will have to wait, or a colleague will have to take up the job, creating a backlog in his/her roaster. In the end, the delayed hairdresser will have to pick up the slack of the colleague that ended up having a backlog.

We investigate this hypothesis in two ways. First we investigate whether the elasticity coefficient varies across working areas, i.e. industrial and non-industrial. Second, we investigate the cross-sectional variation according to employment. Using information on the area information by postal code: residential, industrial, central business district, we classify the work location of each individual in the sample as industrial or other. The variable *Industry* is equal to 1 when the postal code is set industrial, and zero otherwise. The results in column (7) of Table 8 show that working in an industrial area does not have a longer travel time, accounting for both time and individual fixed effects. However, the interaction term of industry and travel time is large and negative. This implies that individuals working in industrial jobs do not exhibit a positive elasticity to commuting time. Indeed, the size of the coefficient of the interaction term is so large that the total coefficient for industrial workers is negative. Overall, in the manufacturing industry the relation between commute time and labor supply is negative, which implies that individuals internalize commute time as part of working time. In services jobs, which are mainly located in the CBD, this relation is large and positive, resulting in substantial amount of unpaid overtime and decrease in efficiency.

Second, we use the cross-sectional variation in individual occupations from the HIT survey to explain the sign and size of the elasticity coefficient. We investigate the relation between the beta of the regression of market time on travel time, in column (1) of Table 8, and individual characteristics and professions. We attach the individual's home postal code and block to those reported in the HIT survey. We match an individual's characteristics with the characteristics of the block, as measured by the HIT survey and described in section 2.7. We construct a variable that aggregates all manufacturing professions into one, '% Manufacturing', which is the percentage all the manufacturing related professions (Plant machine operator assembly, Technician, and Craftsman) to all professions, as described in Section 2.7. While % Manufacturing is measured at the block level, we also use an individual industry related variable, 'Industry Dummy', which is equal to 1 when the postal code is set industrial, and zero otherwise.

Table 15 presents a cross-sectional regression of the elasticity coefficient and several individual and block characteristics. We control for other variables that might affect the elasticity coefficient, like age, ethnicity, and type of work permit. Most importantly, we control for average block income, as Bick, Fuchs-Schündeln, and Lagakos (2018) show that number or hours worked varies with income.

We find that the elasticity of work time to travel time is unaffected by the income level of the individuals. Older individuals exhibit less elasticity coefficient, implying that as one grows older it becomes less important to make up for commute time. However, this coefficient is economically small. Individuals with large families have a larger elasticity. In terms of ethnicity, all ethnicities have a lower coefficient in comparison to Chinese.

The coefficients for both % Manufacturing and Industry dummy are negative, large and statistically significant. Individuals in the manufacturing industries have a lower beta, 0.16, in comparison to those in all other professions. Also, individuals working in an industrial location have a negative beta, -0.91, in comparison to those working in other areas. These results imply that individuals in the service industry, where there are interactions with the consumers or interactive workplace have a large and positive coefficient. Individuals in jobs the manufacturing industry, with fixed outcomes have large and negative coefficients. Thus, the interactive nature of the workplace appears to be the driving force behind the positive elasticity of work time to commute time. If there is a fixed number of appointments that need to be rescheduled and one arrives late to work, this causes a knock-on effect on other tasks that forces one to work longer until all tasks are accomplished. Given the move towards more service-based jobs, this effect will increase on average in the years to come.

5. Conclusions

This paper explores the relation between commute and working time. We use a unique dataset that records *all* commuting trips by public transport (bus and train) over three months in 2013 to study if commuting time affects labor supply decisions in Singapore. We propose a new measure of commuting and working time based on administrative data, which sidesteps issues related to survey data. We document a causal positive relation between commute time and the labor supply decision within individuals. Specifically, we show that a one standard deviation increase in commute time increases working time by 2.2%, controlling for individual, location, and time fixed effects.

First, we show that survey recollections of travel times are biased downward for individuals that are travel passengers. Second, we find that there are two sources of variation in the elasticity of work time to travel time: across individual and within individual (time variation). While part of the cross-sectional variation may be captured by survey data, the time-variation is completely unexplored. First, we find that the cross-sectional variation depends on whether one engages in a service or manufacturing type of job. This cross-sectional variation might be missed out in survey-based responses due to a different selection process, based say on the proportion of industries in the S&P500. Second, we find that there is very large within individual variation in the elasticity, not based on calendar effects, like day of the week or month. The earlier an individual intends to start work the more sensitive they are to travel delays. As the number of delayed/late arrivals to work increases, the more sensitive an individual becomes to travel delays. This within individual variation in elasticity cannot be captured by survey data, which normally survey one individual either in a day or in a week, if such situations do not arise and cannot be compared with other weeks or months.

We find that the relation between travel and working is negative for manufacturing jobs and positive for service jobs. These findings align with travel shocks affecting the productivity of individuals in settings where interaction with colleagues and clients. The presence or absence of peers alters the production process (which in turn will affect consumption, at least in the service industry). Therefore, in professions where interaction among co-workers and with the customers is necessary, disruptions in travelling to work will cause a backlog and increase the working hours beyond the original travel delay. These results imply that employers need to build in mechanisms that can absorb these negative shocks to the work group and minimize the disruption to the work process that derives from commute delays.

References

Aguiar, Mark and Erik Hurst (2007) Measuring trends in leisure: The allocation of time over five decades, *Quarterly Journal of Economics* 122, 969-1006.

Aguiar, Mark, Erik Hurst, and Loukas Karabarbounis (2012) Recent developments in the economics of time use, *Annual Review of Economics* 4, 373-397.

Anderson, T. W. and Herman Rubin (1949) Estimation of the parameters of a single equation in a complete system of stochastic equations, *Annals of Mathematical Statistics* 20, 46–63.

Becker, Gary S. (1965) A theory of the allocation of time. *The Economic Journal* 75, 493-517.

Bick, Alexander, Bettina Brüggemann, and Nicola Fuchs-Schündeln (2016) Hours worked in Europe and the US: New data, new answers, *Scandinavian Journal of Economics,* forthcoming.

Bick, Alexander, Bettina Brüggemann, and Nicola Fuchs-Schündeln (2017) A note on data revisions of aggregate hours worked series: Implications for the Europe-US hours gap, Working Paper.

Bick, Alexander, and Nicola Fuchs- Schündeln (2017) Quantifying the disincentive effects of joint taxation on married women's labor supply, *American Economic Review* 107, 100-104.

Bick, Alexander, and Nicola Fuchs- Schündeln (2018) Taxation and labor supply of married couples across countries: A macroeconomic analysis, *Review of Economic Studies*, forthcoming.

Bick, Alexander, Nicola Fuchs-Schündeln, and David Lagakos (2018) How do hours worked vary with income? Cross-country evidence and implications, *American Economic Review* 108, 170-199.

Bound, John, David A. Jaeger, and Regina M. Baker (1995) Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak, *Journal of the American Statistical Association* 90, 443–450.

Burda, Michael, Katie R. Genadek, and Daniel S. Hamermesh (2016) Not working at work: Loafing, unemployment and labor productivity, NBER Working Paper 21923.

Burda, Michael, Katie R. Genadek, and Daniel S. Hamermesh (2017) Racial/Ethnic differences in non-work at work, NBER Working Paper 23096.

Cameron, A Collin, Jonah B. Gelbach and Douglas L. Miller (2011) Robust inference for multiway clustering, *Journal of Business and Economic Statistics* 29, 238-249.

CNBC (2013) World's most expensive car market just got pricier, http://www.cnbc.com/id/100525565.

CNN (2013) What are the world's best metro systems? Edward Falzon http://travel.cnn.com/explorations/life/10-best-metro-systems-746919/.

Cogan, John F. (1981) Fixed costs and labor supply, *Econometrica* 49, 945–963.

Coviello, Decio, Andrea Ichino, and Nicola Persico (2014) Time allocation and task juggling, *The American Economic Review* 104, 609-623.

Coviello, Decio, Andrea Ichino, and Nicola Persico (2015) The inefficiency of worker time use, *Journal of the European Economic Association* 13, 906-947.

Ehrenberg, Ronald G. and Robert S. Smith (2014) Modern labor economics: Theory and public policy, Pearson Education Limited.

Hamermesh, Daniel S. (2016) What's to know about time use? *Journal of Economic Surveys* 30, 198–203.

Juster, Thomas F. and Frank P. Stafford (1991) The allocation of time: Empirical findings, behavioral models, and problems of measurement, *Journal of Economic Literature* 29, 471-522.

Kahneman, Daniel, Alan B. Krueger, David A. Schkade, Norbert Schwarz, Arthur A. Stone (2004) A survey method for characterizing daily life experience: The day reconstruction method (DRM), *Science* 306, 1776–1780.

LTA (2012) Singapore land and transport statistics in brief, https://www.lta.gov.sg/content/dam/ltaweb/corp/PublicationsResearch/files/FactsandFigures/Stats_in_Brief_2012.pdf.

LTA (2013) Household interview travel survey 2012: Public transport mode share rises to 63% http://www.lta.gov.sg/apps/news/page.aspx?c=2&id=1b6b1e1e-f727-43bb-8688-f589056ad1c4.

McKenzie, Brian and Melanie Rapino (2011) Commuting in the United States: 2009, American Community Survey Reports, US Census Bureau.

Novaco, Raymond W. and Oscar I. Gonzalez (2009) Commuting and well-being, in Yair Amichai-Hamburger (Ed.) Technology and Well-Being. Cambridge University Press.

Prakasam, S. (2008) The Evolution of e-payments in Public Transport – Singapore's Experience, *Japan Railway & Transport Review* 50, 36-39.

Sanderson, Eleanor and Frank Windmeijer (2016) A weak instrument -test in linear IV models with multiple endogenous variables, *Journal of Econometrics* 190, 212-221.

Tuang, Kwong Feng (2015) Less travel, less transport woes https://www.reach.gov.sg/participate/discussion-forum/archives/2015/10/25/less-travel-less-transport-woes.

Zamparini, Luca and Aura Reggiani (2007) Meta-analysis and the value of travel time savings: A transatlantic perspective in passenger transport, *Network Spatial Economics* 7, 377.

Table 1
Travel Purpose

The table presents the travel purpose as described by travelers in the HIT survey in 2008 and 2012.

	2008		2012	
	Frequency	Percent	Frequency	Percent
Accompanying someone	665	0.86	438	0.57
Dining, refreshment	1,639	2.12	2,037	2.65
Education	9,763	12.66	8,918	11.61
Entertainment- Social	137	0.18	248	0.32
Household activities			35,499	46.21
Medical visit (self)	349	0.45	312	0.41
National service			50	0.07
Other Personal Business	606	0.79	753	0.98
Pick-up Drop Off	4,670	6.05	4,076	5.31
Professional Driver			12	0.02
Recreation	384	0.5	508	0.66
Religious related matters	286	0.37	276	0.36
Shopping	2,246	2.91	3,305	4.3
Work Related Trip			420	0.55
Working for paid employment	18,394	23.84	18,806	24.48
Work-related (meetings, sales, etc.)	1,459	1.89	1,159	1.51
Return home	34,451	44.66		
Social visit/gathering	1,825	2.37		
Sports/exercise	250	0.32		
Transfer mode	72	0.09		

Table 2

Mode of Transport by Income Group

The table presents the mode of transport used by different income groups, as reported in the HIT survey in 2008 and 2012. The last column, Pub. Trans., represents the percentage of the public that uses either form of public transport (underground (MRT), light rail (LRT) and public bus).

Income Group	Car	Comp. bus	Cycle	LRT	MRT	Motor cycle	Public bus	School bus	Shuttle bus	Taxi	Van	Pub. Trans. (MRT+LRT+BUS)
Panel A. 2008												
Total	24.3	4.8	2.3	1.9	18.5	4.7	37.9	0.0	0.7	2.4	2.7	58.2
1-1000	4.0	7.5	7.0	0.7	12.3	3.5	62.2	0.0	0.2	0.7	2.0	75.1
1001-1499	3.7	8.5	5.0	1.2	17.6	5.5	51.7	0.0	0.3	1.3	5.3	70.5
1500-1999	8.8	6.6	2.8	1.9	20.9	8.0	45.1	0.1	0.1	1.2	4.8	67.8
2000-2499	16.3	6.0	2.2	1.7	20.4	7.6	40.0	0.0	0.3	1.9	3.6	62.1
2500-2999	24.0	4.7	1.7	1.8	21.3	5.8	35.1	0.0	0.6	2.7	2.4	58.1
3000-3999	30.1	3.1	1.0	1.8	22.2	2.9	33.3	0.0	0.9	2.7	2.0	57.3
4000-4999	39.9	3.0	1.0	2.7	19.9	1.9	27.4	0.0	1.0	2.9	0.3	50.0
5000-5999	47.8	0.9	0.9	2.4	18.1	0.9	25.6	0.0	0.2	3.1	0.2	46.0
6000-6999	52.5	2.0	0.5	1.5	17.2	0.5	20.7	0.0	2.5	2.5	0.0	39.4
7000-7999	63.3	0.0	0.0	0.9	14.7	0.0	20.2	0.0	0.0	0.9	0.0	35.8
>8000	69.2	0.3	1.1	0.5	11.2	1.1	9.0	0.0	1.4	6.0	0.3	20.7
Panel B. 2012												
Total	19.4	5.1	1.4	1.4	29.3	3.6	34.6	0.0	1.4	1.7	2.1	65.3
1-1000	2.0	5.3	6.1	2.8	17.4	3.3	60.4	0.3	0.3	0.8	1.3	80.6
1001-1499	3.1	10.7	3.6	1.7	26.2	3.6	47.0	0.0	0.7	0.4	3.0	74.9
1500-1999	4.9	5.4	1.7	2.3	30.3	5.5	43.6	0.0	1.3	1.3	3.7	76.2
2000-2499	8.8	5.6	1.4	1.4	33.1	6.3	36.8	0.0	1.9	1.2	3.5	71.3
2500-2999	13.0	6.7	1.6	1.1	32.1	5.1	35.4	0.0	1.1	1.2	2.2	68.6
3000-3999	19.8	6.4	0.8	1.9	32.6	3.3	30.8	0.0	1.5	1.2	1.7	65.3
4000-4999	31.3	6.1	0.1	1.4	28.8	2.5	25.3	0.0	1.2	2.2	1.0	55.5
5000-5999	41.2	3.5	0.4	1.0	28.5	1.3	19.9	0.0	1.9	1.9	0.3	49.4
6000-6999	35.7	3.0	0.0	1.0	27.2	2.0	24.3	0.0	2.6	3.6	0.3	52.5
7000-7999	47.6	5.4	0.5	0.5	23.2	0.5	17.8	0.0	2.2	2.2	0.0	41.6
>8000	49.6	1.4	0.2	0.7	19.7	1.6	16.6	0.0	3.1	6.6	0.0	37.0

Table 3
Survey Based In Vehicle Commute Time

The table shows individual reported travel time in 2004, 2008, and 2012 using the HIT survey data. The car driver and passenger, van driver and passenger, and motorcycle rider and passenger are matched to be from the same household and start from the same location.

Traveller	2004	2008	2012
Car driver	21.7	22.0	25.6
Car passenger	18.3	18.8	20.1
Company bus	26.6	25.9	28.9
Cycle	13.6	15.1	15.1
LRT	7.0	9.0	8.8
MRT	22.7	26.1	22.8
Motorcycle rider	23.0	23.7	27.7
Motorcycle passenger	18.4	18.8	25.4
Others		19.6	56.5
Public bus	18.5	19.1	18.2
School bus	23.7	26.4	28.8
Shuttle bus		14.7	19.1
Taxi	18.1	19.2	115.7
Van / Truck driver	24.2	25.6	80.7
Van / Truck passenger	20.9	23.6	38.7

Table 4
EZ-Link Summary Statistics

The table shows the number of individual-trip observations using EZ-Link cards broken down by travelling group and means of transport for the period August-October 2013.

Total	517,203,122
Adults	410,644,827
Children/student	54,033,845
Senior citizen	52,524,450
Bus %	61.56
Mrt %	38.44

Table 5
EZ-Link Time Preliminary Statistics

The table reports the preliminary statistics of daily market time, travel time and estimated income based on block closest to the bus stop classified as "home" for all adults with 25 or more working days. The sample includes 652,936 working individuals.

Variable	**Mean**	**Median**	**Std. Dev.**
Average Market Time (hrs)	10.01	10.35	2.68
Average Travel Time (mins)	30.07	27.88	17.25
Average Income (SGD)	3,334.71	2,878.21	1,848.95

Table 6
Market Time by Township

The table shows the mean and median market and travel time by township. We merge the individuals by the township of the identified home, as described in Section 2.

		Median		Mean	
Township	Obs	Market Time (Hrs)	Travel Time (Mins)	Market Time (Hr)	Travel Time (Mins)
ANG MO KIO	1,213,386	10.3	28.1	10.1	29.2
BEDOK	1,552,868	10.3	25.1	10.0	27.6
BISHAN	565,293	10.1	24.8	9.7	26.1
BOON LAY	5,086	10.4	23.8	9.2	29.4
BUKIT BATOK	813,400	10.4	30.9	10.0	31.5
BUKIT MERAH	894,985	10.2	18.1	9.8	22.0
BUKIT PANJANG	474,525	10.3	35.1	9.8	36.4
BUKIT TIMAH	197,317	10.0	23.9	9.4	25.5
CENTRAL WATER	2,980	9.7	25.6	9.0	27.5
CHANGI	51,912	10.4	25.8	10.0	30.3
CHOA CHU KANG	1,052,315	10.4	35.8	10.0	36.3
CLEMENTI	549,196	10.3	23.8	10.0	25.6
DOWNTOWN CORE	223,483	10.3	18.8	10.0	23.2
GEYLANG	1,249,009	10.7	22.4	10.5	25.7
HOUGANG	1,257,333	10.3	28.0	10.0	28.9
JURONG EAST	585,611	10.3	29.9	10.0	30.6
JURONG WEST	1,872,435	10.4	32.4	10.1	32.9
KALLANG	753,262	10.3	19.3	10.1	22.7
LIM CHU KANG	728	10.4	56.2	10.2	54.0
MANDAI	7,021	10.2	26.3	10.0	30.4
MARINA SOUTH	842	10.5	23.6	9.6	27.4
MARINE PARADE	152,037	10.3	26.2	10.0	28.6
MUSEUM	31,036	10.1	11.5	9.7	17.2
NEWTON	66,135	10.1	12.9	9.7	15.4
NORTH-EASTERN	120	10.3	31.5	10.5	35.6
NOVENA	245,317	10.2	18.9	9.8	22.3
ORCHARD	84,126	10.2	13.2	9.7	18.6
OUTRAM	140,124	10.2	18.6	9.8	22.0
PASIR RIS	593,996	10.3	34.6	9.9	34.4
PAYA LEBAR	11,096	11.5	34.6	10.8	37.2
PIONEER	42,605	11.3	36.9	11.0	36.2
PUNGGOL	484,398	10.3	35.7	9.7	34.4
QUEENSTOWN	664,027	10.2	19.4	9.8	22.6
RIVER VALLEY	27,682	10.0	15.7	9.6	19.4
ROCHOR	317,839	10.7	18.1	10.4	21.8
SELETAR	1,397	10.4	34.4	9.8	35.1
SEMBAWANG	663,787	10.5	39.5	10.2	37.3
SENGKANG	1,162,505	10.3	32.4	9.8	32.1
SERANGOON	421,338	10.2	26.1	9.8	27.5
SINGAPORE RIVER	13,598	10.2	18.5	9.5	22.2
SOUTHERN ISLAND	2,343	10.0	20.9	9.7	22.0
STN SERANGOON	264,600	10.2	24.6	9.9	25.7
SUNGEI KADUT	210,425	11.4	34.7	11.2	35.4
TAMPINES	1,349,500	10.3	31.9	9.9	32.4
TANGLIN	49,055	9.9	18.1	9.4	20.7
TENGAH	1,008	10.5	28.0	9.9	32.5
TOA PAYOH	1,038,577	10.2	21.0	9.9	23.3
TUAS	9,386	10.3	32.0	9.8	36.8
WESTERN WATER	17,830	11.0	47.1	10.5	46.6
WOODLANDS	1,661,004	10.5	40.9	10.2	39.1
YISHUN	1,429,098	10.37	35.6	10.2	35.2
Total/Average	24,478,976	10.4	27.3	10.0	29.3

Table 7
Extensive Margin

The table presents estimates of the linear probability model regression of a work dummy variable on rain, travel distance, mean of transport, and day of the week. *Avg. Rain Duration* is the average length of rain at the home boarding location between 7 and 9 AM, *Avg. Rain Amount* is the average amount of rain at the home boarding location between 7 and 9 AM, *Max. Rain Duration* is the longest rain duration at the home boarding location between 7 and 9 AM, *Max. Rain Amount* is the largest amount of rain at the home boarding location between 7 and 9 AM, *Travel by Bus* is a dummy equal to 1 if the commuter uses bus, *Avg. Travel Time* is the average commute time for the individual in the sample, *Vehicle Available* is an indicator variable of whether the individual owns a car in the household. There is day of the week fixed effects. Rain information comes from the national weather service data for the nearest weather station. Standard errors are double clustered at the individual and day level, following Cameron, Gelbach and Miller (2011). *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Avg. Rain Duration	-0.01*		-0.01**	
	(-1.74)		(-2.32)	
Avg. Rain Amount	0.01		0.01	
	(1.09)		(1.47)	
Max. Rain Duration		-0.00		-0.00**
		(-1.55)		(-2.07)
Max. Rain Amount		0.00		0.00
		(0.55)		(0.78)
Max Travel Distance			0.00***	0.00***
			(35.43)	(29.28)
Travel by Bus			-0.04***	-0.04***
			(-36.30)	(-37.75)
Avg. Travel Time			0.00	0.00
			(0.13)	(0.20)
Vehicle Available			0.00***	0.00***
			(7.08)	(6.58)
Tuesday	-0.01	-0.02	-0.01	-0.02
	(-0.37)	(-0.55)	(-0.51)	(-0.74)
Wednesday	0.00	0.00	0.01	0.00
	(0.30)	(0.26)	(0.44)	(0.38)
Thursday	-0.03	-0.03	-0.03	-0.03
	(-1.02)	(-0.99)	(-1.35)	(-1.32)
Friday	-0.06*	-0.06*	-0.06**	-0.06**
	(-1.86)	(-1.88)	(-2.46)	(-2.48)
Intercept			0.60***	0.60***
			(78.08)	(71.36)
N	4.65e+07	4.65e+07	4.21e+07	4.21e+07
Adj. R^2	0.14	0.14	0.01	0.01
Individual FE	YES	YES	NO	NO
Time FE	NO	NO	NO	NO
Double Cluster Error	YES	YES	YES	YES

Table 8
Regression Results of Market on Travel Time

The table presents regressions of market time (time spent at work in minutes) and travel time (time taken to get to work) and control variables. The regression is a panel regression with individual and travel day fixed effects. "Start early" is a dummy variable indicating when an individual starts work 30 minutes before her average starting time. "Start late" is a dummy variable indicating when an individual starts work 30 minutes after her average starting time. "Peak Hour" is a dummy variable that indicates when a trip starts during peak hours (7-9 am). "Heavy rain" and "Heavy at Alight" are dummy variables for rain over 7mm at the starting station at the beginning and at the end of the working day, respectively. Rain information is from the national weather service data for the nearest weather station. "Lag Dep. Var." is the lagged dependent variable, market time. "Industry" is a dummy variable equal to 1 if the individual works in an industrial estate, an zero otherwise. T-statistics are presented in parenthesis, and standard errors are double clustered at the individual and travel day level. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Travel Time	0.74***	0.80***	0.63***	0.69***	0.69***	0.69***	0.89***
	(71.92)	(76.77)	(59.66)	(61.64)	(60.58)	(60.22)	(71.18)
Peak Hour		82.16***		12.58***	12.60***	12.04***	8.66***
		(64.08)		(20.4)	(20.44)	(19.28)	(14.09)
Peak Hour * Travel Time		-0.01***		-0.01***	-0.01***	-0.01***	-0.01***
		(-26.38)		(-30.45)	(-30.44)	(-30.15)	(-23.37)
Start Early			15.22***	14.45***	14.52***	14.37***	15.77***
			(29.58)	(28.97)	(28.62)	(28.57)	(31.5)
Travel*Start Early			0.01***	0.01***	0.01***	0.01***	0.01***
			(38.75)	(40.7)	(40.46)	(40.69)	(37.95)
Start Late			-147.12***	-145.46***	-145.50***	-143.47***	-143.09***
			(-124.77)	(-124.15)	(-124.51)	(-122.03)	(-120.55)
Travel*Start Late			0.00***	0.00	0.00	0.00	0.00
			(4.78)	(1.35)	(1.37)	(1.39)	(0.61)
Heavy Rain					-29.2	-28.71	-28.71
					(-1.66)	(-1.65)	(-1.64)
Travel*Heavy Rain					0.00	0.00	0.01
					(1.34)	(1.35)	(1.34)
Heavy at Alight					-17.17	-16.58	-16.45
					(-1.57)	(-1.54)	(-1.52)
Travel*Heavy Rain at Alight					0.00	0.00	0.00
					(0.43)	(0.46)	(0.46)
Lag Dep. Var.						0.04***	0.04***
						(12.73)	(12.74)
Industry							119.12
							(0.87)
Travel*Industry							-0.02***
							(-67.61)
Stock FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
Double Cluster Error	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.60	0.61	0.67	0.67	0.67	0.68	0.68

Table 9
Time Series Delay Analysis

The table shows the panel regression for different early and late arrival times. We account for several early and late arrival times, up to 15 minutes "(<15min)", between 15 and 30 minutes "(15-30min)", up to 30 minutes "(<30min)", more than 30 minutes "(>30min)", between 30 and 60 minutes "(30-60min)", and more than 1 hour "(>60min)". We suppress the following control variables to save space: peak hour and travel time*peak hour. T-statistics are presented in parenthesis, and standard errors are double clustered at the individual and travel day level. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Travel Time	0.44***	0.40***	0.64***	0.37***
	(44.92)	(40.74)	(61.62)	(37.60)
Start Early (<15min)		6.40***		5.79***
		(46.66)		(42.63)
Travel*Start Early (<15min)		0.06***		0.06***
		(17.75)		(17.86)
Start Early (15-30min)		13.86***		11.25***
		(42.64)		(35.03)
Travel*Start Early (15-30min)		0.31***		0.31***
		(37.34)		(36.73)
Start Early (<30min)	8.28***			
	(44.95)			
Travel*Start Early (<30min)	0.12***			
	(25.90)			
Start Early (>30min)	17.27***	18.72***		
	(32.46)	(34.54)		
Travel*Start Early (>30min)	0.65***	0.70***		
	(41.53)	(43.24)		
Start Early (30-60min)				12.68***
				(25.42)
Travel*Start Early (30-60min)				0.64***
				(44.57)
Start Early (>60min)			3.99***	5.49***
			(6.32)	(8.05)
Travel*Start Early (>60min)			0.55***	0.78***
			(26.98)	(34.47)
Start Late (<15min)		-7.99***		-7.87***
		(-50.36)		(-48.96)
Travel*Start Late (<15min)		-0.01***		-0.01
		(-3.26)		(-1.46)
Start Late (15-30min)		-29.33***		-27.19***
		(-56.42)		(-50.52)
Travel*Start Late (15-30min)		0.04***		0.06***
		(4.81)		(6.27)
Start Late (<30min)	-11.85***			
	(-56.90)			
Travel*Start Late (<30min)	-0.01			
	(-1.45)			
Start Late (>30min)	-139.65***	-139.01***		
	(-121.42)	(-117.82)		
Travel*Start Late (>30min)	0.21***	0.26***		
	(13.35)	(16.26)		
Start Late (30-60min)				-54.53***
				(-58.57)

Travel*Start Late (30-60min)				0.18***
				(13.28)
Start Late (>60min)			-178.09***	-177.57***
			(-154.72)	(-143.35)
Travel*Start Late (>60min)			-0.03*	0.27***
			(-1.81)	(14.87)
Control Variables	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Double Cluster Error	YES	YES	YES	YES
N	2.55e+07	2.55e+07	2.55e+07	2.55e+07
R2	0.677	0.678	0.680	0.686

Table 10
Serial Delay Analysis

The table shows the panel regression for different numbers of delayed arrivals to work. 1st Late is a dummy variable equal to 1 for the first delayed arrival to work in the month, 2nd Late is a dummy variable equal to 1 for the second delayed arrival to work, 3rd Late is a dummy variable equal to 1 for the third or more delayed arrival to work. Effect is the combined Travel Time and Delayed Arrival effect. Regressions (2) and (3) include control variables, not reported: peak hour and travel time*peak hour. T-statistics are presented in parenthesis, and standard errors are double clustered at the individual and travel day level. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	(1)		(2)		(3)	
		Effect		Effect		Effect
Travel Time	0.76***		0.60***		0.66***	
	(74.35)		(61.53)		(63.46)	
1st Late	11.96***		126.66***		-35.60***	
	(7.04)		(66.16)		(-17.78)	
Travel*1st Late	-1.07***	-0.31	-0.55***	0.05	-0.33***	0.33
	(-29.39)		(-12.08)		(-8.46)	
2nd Late	15.78***		121.20***		-33.50***	
	(8.59)		(63.84)		(-15.93)	
Travel*2nd Late	-0.89***	-0.13	-0.24***	0.36	-0.12***	0.54
	(-24.81)		(-5.90)		(-2.92)	
3rd Late	15.92***		111.78***		-31.33***	
	(6.08)		(38.72)		(-10.39)	
Travel*3rd Late	-0.77***	-0.01	0.00	0.60	-0.04	0.62
	(-15.89)		(0.05)		(-0.61)	
Start Early (>30min)			14.25***			
			(27.96)			
Travel*Start Early (>30min)			0.53***			
			(35.13)			
Start Early (>60min)					4.28***	
					(6.72)	
Travel*Start Early (>60min)					0.51***	
					(24.11)	
Start Late (>30min)			-134.44***			
			(-113.83)			
Travel*Start Late (>30min)			-0.42***			
			(-21.72)			
Start Late (>60min)					-178.27***	
					(-155.25)	
Travel*Start Late (>60min)					-0.05**	
					(-2.65)	
Controls	NO		YES		YES	
Individual FE	YES		YES		YES	
Time FE	YES		YES		YES	
Double Cluster Error	YES		YES		YES	
N	2.55e+07		2.55e+07		2.55e+07	
Adj. R^2	0.601		0.677		0.680	

Table 11
Beta by Township

The table shows the beta of the simple regression of market time on travel time (Column 1 in Panel A of Table 8) by township.

Township	Beta
No Township	1.12
ANG MO KIO	1.18
BEDOK	0.83
BISHAN	1.31
BOON LAY	2.09
BUKIT BATOK	1.27
BUKIT MERAH	0.26
BUKIT PANJANG	0.96
BUKIT TIMAH	0.59
CENTRAL WATER	-0.47
CHANGI	0.03
CHOA CHU KANG	1.57
CLEMENTI	0.85
DOWNTOWN CORE	0.59
GEYLANG	0.39
HOUGANG	1.16
JURONG EAST	1.28
JURONG WEST	1.62
KALLANG	0.24
LIM CHU KANG	-0.87
MANDAI	2.39
MARINA EAST	5.86
MARINA SOUTH	-0.50
MARINE PARADE	0.64
MUSEUM	1.27
NEWTON	0.11
NORTH-EASTERN	7.83
NOVENA	0.66
ORCHARD	1.06
OUTRAM	0.16
PASIR RIS	1.56
PAYA LEBAR	-0.41
PIONEER	1.46
PUNGGOL	1.91
QUEENSTOWN	0.67
RIVER VALLEY	-0.51
ROCHOR	0.03
SELETAR	1.47
SEMBAWANG	1.91
SENGKANG	1.66
SERANGOON	1.10
SINGAPORE RIVER	0.72
SOUTHERN ISLAND	-0.87
STN SERANGOON	1.45
SUNGEI KADUT	0.71
TAMPINES	1.28
TANGLIN	0.68
TENGAH	1.61
TOA PAYOH	0.72
TUAS	0.70
WESTERN ISLAND	-1.50
WESTERN WATER	0.59
WOODLANDS	1.59
YISHUN	1.53
	1.03

Table 12
IV Regression

The table shows the 2nd stage of a two stage least squares regression of market time on travel time. The instruments for travel time are: the amount of rain in the next hour after start of travel (1), the amount of rain in the current hour of travel (2), a heavy rain dummy in the current hour of travel (3) and a heavy rain dummy in the next hour after start of travel (4). "Start early" is a dummy variable indicating when an individual starts work 30 minutes before her average starting time. "Start late" is a dummy variable indicating when an individual starts work 30 minutes after her average starting time. "Peak Hour" is a dummy variable that indicates when a trip starts during peak hours (7-9 am). T-statistics are presented in parenthesis, and standard errors are double clustered at the individual and travel day level. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. F-test is the Sanderson-Windmeijer (SW) F-statistic for weak identification. Anderson-Rubin Wald is the Anderson-Rubin Wald test F-statistic for weak identification. P-values are presented in square brackets.

	(1)		(2)		(3)		(4)	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd
Instrument	-0.02***		-0.02***		-0.11***		-0.31***	
	(-24.12)		(-11.31)		(-6.40)		(-22.48)	
Travel Time		2.53***		33.12***		74.91***		5.92***
		(3.40)		(10.19)		(6.29)		(7.54)
Start Early	-12.32***	38.93***	-12.32***	415.86***	-12.32***	930.82***	-12.32***	80.70***
	(-380.30)	(4.24)	(-380.29)	(10.38)	(-380.29)	(6.35)	(-380.29)	(8.33)
Travel*Start Early	0.44***	-0.30	0.44***	-13.85***	0.44***	-32.37***	0.44***	-1.80***
	(457.22)	(-0.91)	(457.22)	(-9.62)	(457.23)	(-6.14)	(457.22)	(-5.17)
Start Late	-20.70***	-101.01***	-20.70***	532.19***	-20.70***	1397.25***	-20.70***	-30.84*
	(-553.52)	(-6.55)	(-553.52)	(7.91)	(-553.51)	(5.67)	(-553.50)	(-1.89)
Travel*Start Late	0.64***	-1.15**	0.64***	-20.71***	0.64***	-47.43***	0.64***	-3.31***
	(569.73)	(-2.41)	(569.72)	(-9.96)	(569.72)	(-6.23)	(569.72)	(-6.59)
Peak Hour	-24.17***	56.75***	-24.17***	796.11***	-24.17***	1806.20***	-24.17***	138.68***
	(-694.70)	(3.15)	(-694.69)	(10.13)	(-694.68)	(6.28)	(-694.70)	(7.30)
Travel *Peak Hour	0.69***	-1.01**	0.68***	-22.00***	0.69***	-50.66***	0.69***	-3.34***
	(857.87)	(-1.98)	(857.85)	(-9.86)	(857.85)	(-6.21)	(857.87)	(-6.19)
Cluster Error	Yes		Yes		Yes		Yes	
Individual FE	Yes		Yes		Yes		Yes	
F-test	581.91	[0.00]	128.02	[0.00]	40.92	[0.00]	505.31	[0.00]
Anderson-Rubin Wald	11.59	[0.00]	402.16	[0.00]	664.01	[0.00]	62.02	[0.00]

Table 13

Falsification Test

The table shows the panel regression for the falsification tests. Panel A shows the regression of lag travel time on market time and Panel B shows the regression of market time on lag travel time. The regressions include individual fixed effects and standard errors are double clustered at individual and day level.

Panel A.	Travel Time *t-1*	
	Coeff.	p-val
Market Time *t*	-0.0001	0.22

Panel B.	Market Time *t*	
	Coeff.	p-val
Travel Time *t-1*	0.0088	0.14

Table 14
Alternative Explanations

The table shows the panel regression of changes in boarding station after work (Ch.Stat.) and a break after work (Break). "Ch.Stat.)" is equal to 1 where there is a change in the leaving work station, and zero otherwise. "Break" is equal to 1 if "Ch. Stat" is equal to 1 and the abnormal working time is more than 1 hour, and zero otherwise. Panel A presents the results conditioning on market and travel time. Panel B presents the results conditioning on abnormal travel time, the difference between travel time on day t and average travel time. The regression includes individual and time fixed effects. T-statistics are presented in parenthesis, and standard errors are double clustered at the individual and travel day level, following Cameron, Gelbach and Miller (2011). *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Effect of market and travel time

	Ch.Stat.	Ch.Stat.	Ch.Stat.	Ch.Stat.	Break	Break	Break	Break
Market Time	-0.00***	-0.00***	-0.00***	-0.00***	0.00***	0.00***	0.00***	0.00***
	(-90.27)	(-90.61)	(-88.95)	(-88.72)	(79.00)	(77.55)	(59.04)	(59.63)
Travel Time	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(-19.37)	(-19.54)	(-20.37)	(-20.34)	(-13.48)	(-13.43)	(-11.20)	(-11.25)
Start Early (>30min)	0.02***				-0.02***			
	(73.70)				(-72.73)			
Start Early (>60min)		0.02***				-0.02***		
		(68.48)				(-67.14)		
Start Early (<15min)			0.00***				-0.00***	
			(10.59)				(-20.12)	
Start Early (<30min)				0.00***				-0.00***
				(27.12)				(-30.46)
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Double Cluster Error	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.49	0.49	0.49	0.49	0.29	0.28	0.28	0.28

Panel B. Effect of abnormal travel time

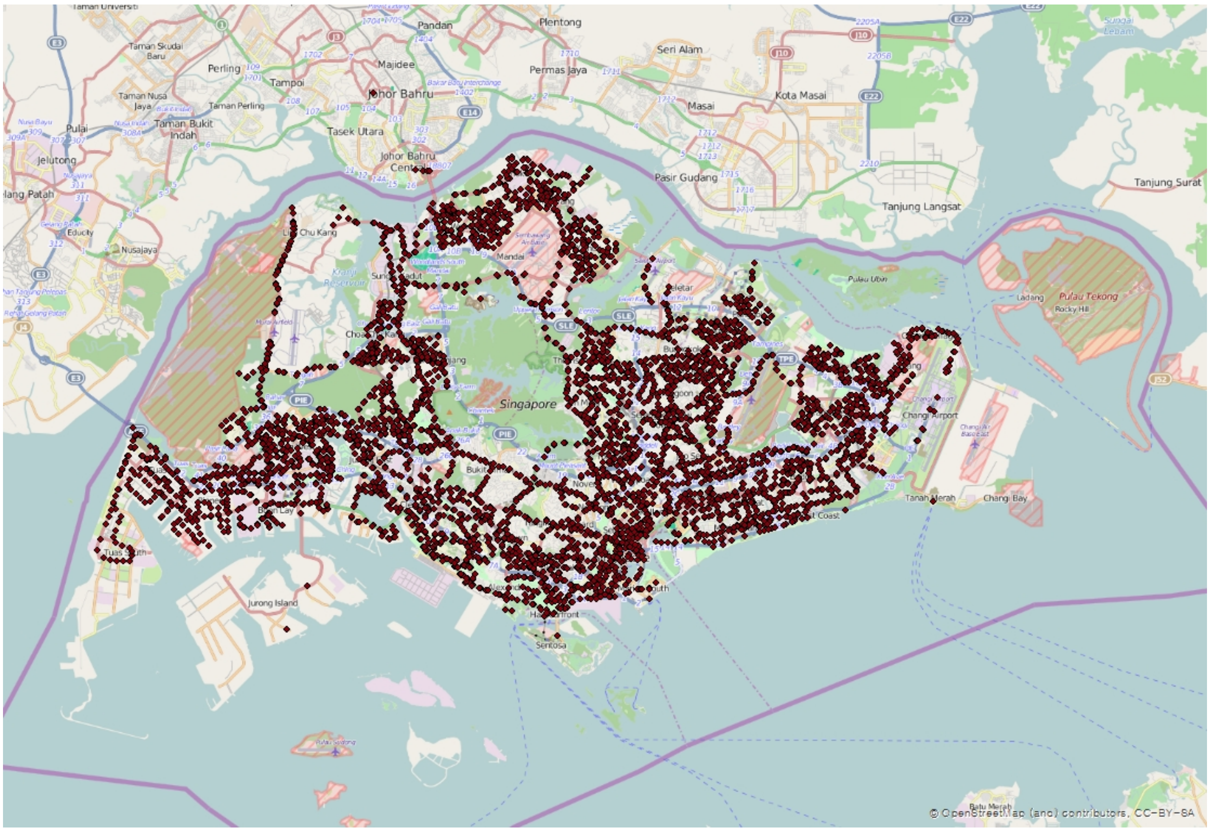
	Ch.Stat.	Ch.Stat.	Ch.Stat.	Ch.Stat.	Break	Break	Break	Break
Start Early (>30min)	0.00***				-0.01***			
	(8.28)				(-57.46)			
Start Early (>60min)		0.00***				-0.02***		
		(10.90)				(-54.29)		
Start Early (<15min)			-0.00***				-0.00***	
			(-12.63)				(-10.03)	
Start Early (<30min)				-0.00***				-0.00***
				(-13.27)				(-16.77)
Abnor. Travel Time	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(-27.55)	(-27.53)	(-27.55)	(-27.54)	(-6.65)	(-6.84)	(-6.29)	(-6.28)
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Double Cluster Error	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.48	0.48	0.48	0.48	0.28	0.28	0.28	0.28

Table 15
Cross sectional regression of commuting time elasticity of labor supply on profession

The table shows the cross sectional regression of individual elasticity of work time to travel time and block characteristics. Block income is the average block income in SGD, Block Age is the average age in the block, Family Size is the average number of members of one family in the block. % Manufacturing is the percentage all the manufacturing related professions (Plant machine operator assembly, Technician, and Craftsman) to all professions, as described in Section 2.7. Industry dummy is equal to 1 if the individual works in an industrial estate, and zero otherwise. The rest of the variables are defined in Section 2.7. Obs. is the number of individuals in the sample. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Intercept	0.35***	0.38***	0.51***
		(4.63)	(5.02)	(6.78)
	Block Income	-0.00***	-0.00***	-0.00***
		(-4.91)	(-5.31)	(-7.51)
	Block Age	-0.01***	-0.01***	-0.01***
		(-10.37)	(-10.33)	(-9.68)
	Family Size	0.08***	0.08***	0.10***
		(9.38)	(9.41)	(11.74)
Ethnicity	%Others	-0.11	-0.12	-0.22***
		(-1.51)	(-1.54)	(-2.92)
	%Malay	-0.27***	-0.23***	-0.26***
		(-6.21)	(-5.36)	(-5.94)
	%Indian	-0.48***	-0.47***	-0.48***
		(-10.28)	(-10.01)	(-10.24)
Type Residence	%Employment Pass	0.22***	0.19**	0.32***
		(2.96)	(2.56)	(4.29)
	%Permanent Resident	-0.04	-0.03	0.01
		(-0.70)	(-0.55)	(0.18)
	%S Pass	-0.21	-0.18	-0.03
		(-1.19)	(-1.03)	(-0.19)
	%Work Permit	-0.04	-0.06	-0.09
		(-0.36)	(-0.58)	(-0.84)
Profession	% Manufacturing		-0.22***	-0.17***
			(-5.05)	(-3.81)
	Industry Dummy			-1.42***
				(-53.55)
	Obs	652,936	652,936	652,936

Figure 1
Map of Public Transport in Singapore



Source: Adapted from URA (2002).

Figure 2
Singapore Population Density by Township

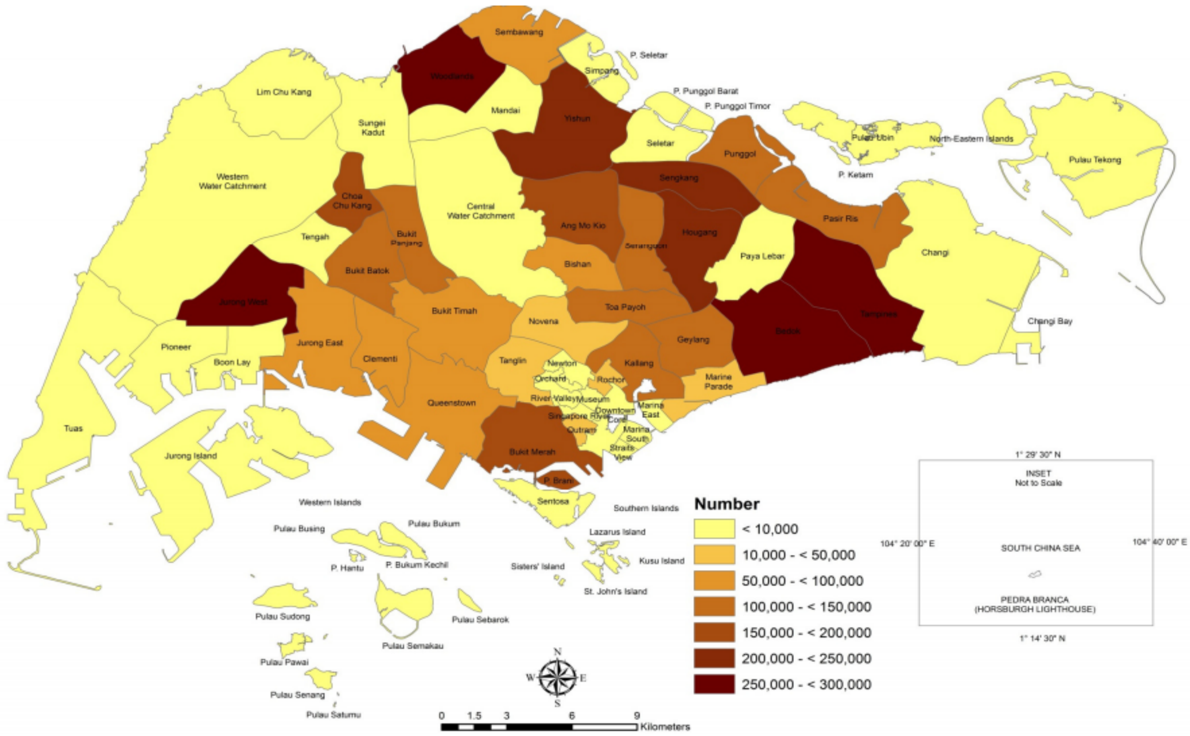


Figure 3

Frequency Table of Travel Time Effect on Market Time by Township

The figure shows distribution the beta reported in Table 11 for each township.

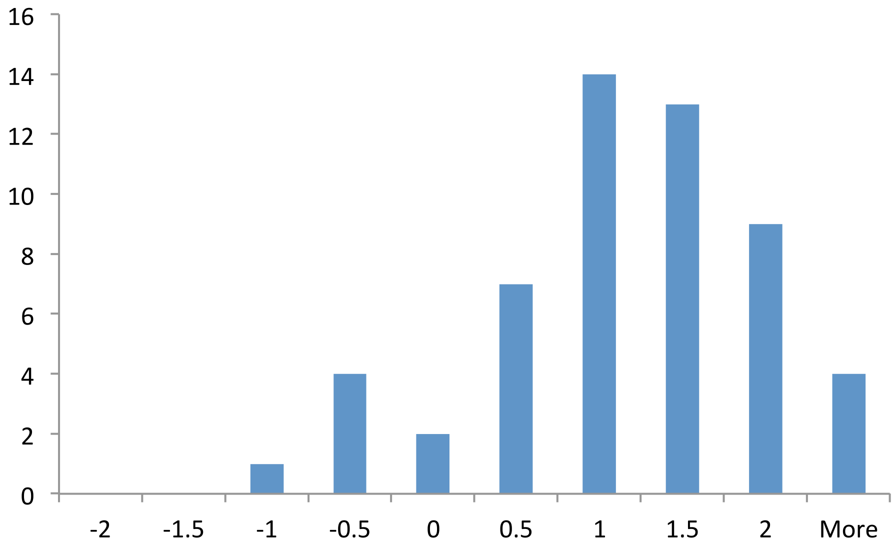
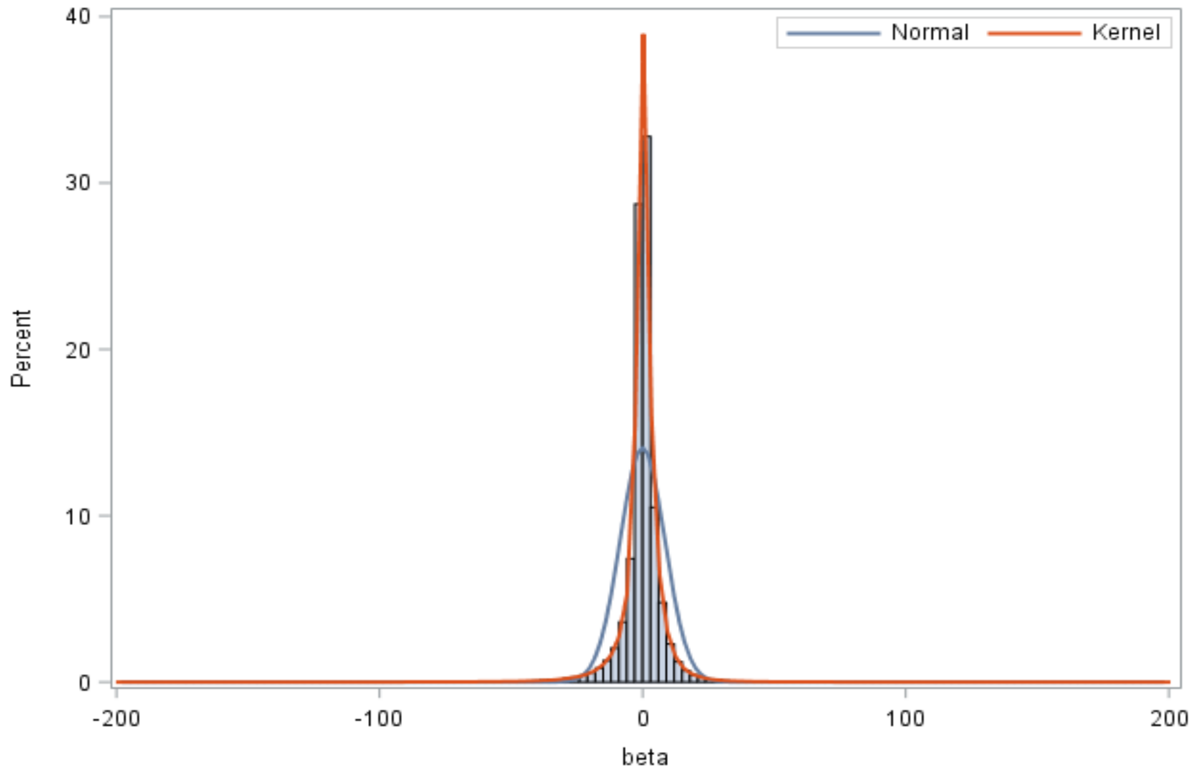


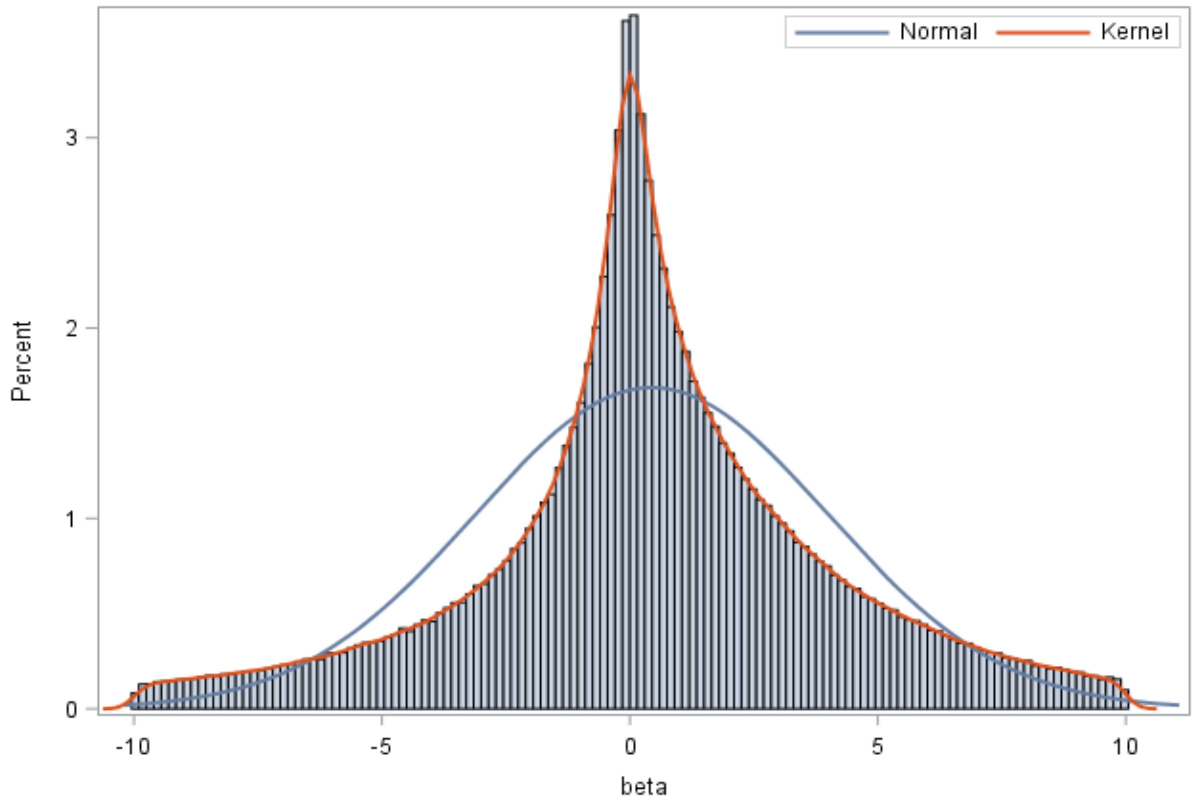
Figure 4
Distribution of Beta by Individual

The figure shows distribution of the beta reported in Table 8 for each individual in the sample. Panel A shows the beta for every individual. Panel B shows the distribution for individuals with betas between -10 and 10.

Panel A. Beta distribution for all individuals



Panel B. Subsample beta distribution



Appendix

Table A1
Number of Weekly Working Hours by Industry

	2013*	Mar	Jun	Sep
INDUSTRY				
MANUFACTURING	50.1	50.2	50.4	50.1
CONSTRUCTION	53.2	53.0	53.4	53.0
SERVICES	43.4	43.4	43.4	43.4
WHOLESALE AND RETAIL TRADE	43.2	43.4	43.5	43.0
TRANSPORTATION AND STORAGE	45.7	45.6	45.4	45.9
ACCOMMODATION AND FOOD SERVICES	43.0	42.4	42.8	43.4
INFORMATION AND COMMUNICATIONS	41.7	41.7	41.7	41.7
FINANCIAL AND INSURANCE SERVICES	41.2	41.2	41.1	41.3
REAL ESTATE SERVICES	44.6	44.7	44.7	44.3
PROFESSIONAL SERVICES	43.6	43.7	43.8	43.6
ADMINISTRATIVE AND SUPPORT SERVICES	47.5	47.3	47.4	47.8
COMMUNITY, SOCIAL AND PERSONAL SERVICES	42.1	42.1	42.1	42.0
OTHERS**	45.7	46.0	45.5	45.9
TOTAL	46.2	46.2	46.3	46.2

Table A2
Distribution of Race by Township

The table shows the distribution by race across townships in Singapore. The data is constructed from the block-level data provided in the HIT 2012 survey. We count the number of survey respondents in each township by race and report the proportion of each race in each township.

Township	% Chinese	% Indian	% Malay	% Other
ANG MO KIO	72.7	12.0	12.6	2.8
BEDOK	63.9	18.9	12.2	5.0
BISHAN	85.8	5.3	3.1	5.8
BUKIT BATOK	67.4	19.2	8.9	4.5
BUKIT MERAH	59.2	27.1	8.4	5.3
BUKIT PANJANG	70.2	8.7	16.9	4.2
BUKIT TIMAH	91.1	5.3		3.7
CHOA CHU KANG	67.9	12.8	14.6	4.6
CLEMENTI	79.4	8.4	5.8	6.4
DOWNTOWN	79.2			20.8
GEYLANG	55.4	19.4	20.6	4.6
HOUGANG	83.0	10.9	5.3	0.8
JURONG EAST	65.9	12.1	14.9	7.0
JURONG WEST	65.1	14.5	15.4	5.1
KALLANG	56.1	26.7	14.6	2.5
MARINE PARADE	61.0	20.6	15.0	3.4
NEWTON				100.0
NOVENA	73.7	9.2	12.0	5.1
OUTRAM	67.0	16.8	12.7	3.5
PASIR RIS	68.4	7.5	16.0	8.1
PUNGGOL	74.6	11.3	10.7	3.4
QUEENSTOWN	78.2	10.4	5.7	5.7
RIVER VALLEY	80.6			19.4
ROCHOR	80.3	16.0	3.8	
SEMBAWANG	69.6	10.0	13.9	6.5
SENGKANG	77.9	10.9	8.4	2.8
SERANGOON	86.4	8.6	1.7	3.3
SINGAPORE RIVER	100.0			
TAMPINES	73.8	9.1	12.9	4.3
TANGLIN	84.2	4.8		11.0
TOA PAYOH	78.2	10.8	7.9	3.1
WOODLANDS	55.9	13.4	27.8	2.9
YISHUN	65.6	16.5	14.1	3.7

Table A3
Occupation Distribution

The table shows the distribution by race across townships in Singapore. The data is constructed from the block-level data provided in the HIT 2012 survey. We count the number of survey respondents in each township by occupation and report the proportion of each occupation in each township.

Township	Associate Professional and Technician	Cleaner, Laborer	Clerical Worker	Legislator, Senior Official, Manager	Plant Machine Operator	Production Craftsmen	Profes-sional	Service and Sales Workers
ANG MO KIO	10.2	10.2	9.5	4.2	4.2	3.1	23.8	33.1
BEDOK	7.8	2.9	6.8	13.2	2.0	3.2	43.8	19.2
BISHAN	2.8	0.7	12.4	9.4	2.4	2.5	48.0	18.6
BUKIT BATOK	11.6	1.8	12.6	15.3	5.1	3.9	31.6	16.0
BUKIT MERAH	13.5	13.0	7.1	6.9	2.8	1.0	29.4	22.8
BUKIT PANJANG	9.8	2.2	15.9	12.1	4.6	2.9	24.1	26.2
BUKIT TIMAH	6.6	1.1	6.4	29.4	0.3	0.3	47.5	6.1
CHOACHU KANG	10.9	2.5	10.3	7.2	3.0	3.4	38.0	21.6
CLEMENTI	5.4	6.0	6.7	12.4	3.3	3.0	47.6	14.2
DOWNTOWN	18.2						18.2	63.6
GEYLANG	7.4	9.9	6.3	13.3	3.9	0.8	36.4	21.2
HOUGANG	11.0	4.6	11.4	13.5	2.8	2.6	23.2	27.7
JURONG EAST	11.9	6.4	10.8	7.1	4.1	4.1	42.4	12.5
JURONG WEST	15.0	7.6	15.1	6.0	4.6	3.8	29.2	17.2
KALLANG	11.6	11.1	8.8	13.1	3.5	1.2	25.9	23.4
MARINE PARADE	9.7	5.5	5.2	17.1	0.7		41.6	18.6
NEWTON			40.0				60.0	
NOVENA	3.7	10.7	4.5	17.5	3.7		20.3	37.9
OUTRAM	13.0	14.2	0.6	7.1		3.6	30.2	27.2
PASIR RIS	7.7	1.0	6.5	6.8	2.8	2.5	43.5	28.3
PUNGGOL	6.3	5.0	10.1	17.6	1.4	2.4	31.0	23.4
QUEENSTOWN	7.5	9.0	9.2	11.4	2.3	0.3	43.7	16.0
RIVER VALLEY	4.0	10.6	4.0	20.0			56.0	16.0
ROCHOR	14.2		9.7	15.0	5.3		16.8	28.3
SEMBAWANG	20.5	1.1	23.8	17.5	1.8	1.3	15.8	14.9
SENGKANG	12.4	2.5	11.3	13.3	4.1	3.4	27.8	23.3
SERANGOON	7.9	2.8	8.7	13.2	2.2	0.9	41.2	21.0
SINGAPORE RIVER							100.0	
TAMPINES	7.9	4.2	8.4	4.9	2.6	2.8	41.4	24.9
TANGLIN	4.4			28.9			57.8	8.9
TOA PAYOH	9.6	8.5	10.5	8.0	2.8	0.7	28.4	30.7
WOODLANDS	12.3	3.1	17.7	13.1	5.7	1.2	23.4	19.6
YISHUN	18.8	4.9	7.8	4.2	5.1	4.1	18.9	33.5

Table A4
Township Distribution by Citizenship

The table shows the distribution by race across townships in Singapore. The data is constructed from the block-level data provided in the HIT 2012 survey. We count the number of survey respondents in each township by citizenship and report the proportion of each citizenship type in each township. S Pass allows mid-level skilled staff to work in Singapore. Candidates need to earn at least $2,200 a month and have the relevant qualifications and work experience. Work Permit allows semi-skilled foreign workers from approved source countries to work in certain sectors. The Employment Pass allows foreign professionals, managers and executives to work in Singapore. Candidates need to earn at least $3,300 a month and have acceptable qualifications. The Dependent's Pass allows spouses and children of Employment Pass or S Pass holders to join them in Singapore.

Township	SG Citizen	Permanent Resident	S Pass	Work Permit	Employment Pass	Foreign Domestic Workers	Dependent Pass
ANG MO KIO	84.6	9.0	0.2	1.1	1.4	1.7	0.8
BEDOK	78.1	11.0	0.7	0.6	2.7	3.4	2.2
BISHAN	90.4	4.0			1.3	4.0	
BUKIT BATOK	78.2	11.7	0.5	0.5	2.6	2.9	1.8
BUKIT MERAH	85.6	5.9	1.4	0.3	2.3	2.1	0.7
BUKIT PANJANG	86.6	7.5	0.4	0.6	0.6	2.5	0.9
BUKIT TIMAH	82.6	6.1	0.2	0.1	1.7	5.9	0.9
CHOA CHU KANG	83.4	11.2	0.5	0.6	0.8	2.3	0.5
CLEMENTI	77.8	14.4	0.9	0.7	1.7	2.1	1.4
DOWNTOWN	79.2				16.7		4.2
GEYLANG	75.3	14.1	1.1	0.7	3.0	2.4	2.1
HOUGANG	89.9	5.8	0.1	0.4	0.8	1.5	1.0
JURONG EAST	80.3	11.7	0.5	0.1	2.7	1.8	1.2
JURONG WEST	79.0	12.7	0.9	1.8	1.3	1.9	0.6
KALLANG	79.0	11.3	0.4	0.4	2.1	2.4	3.5
MARINE PARADE	81.3	9.1	0.6	0.2	2.2	5.1	1.0
NEWTON	38.5	53.8				7.7	
NOVENA	80.8	6.3	1.1	6.0		2.7	0.3
OUTRAM	85.9	6.9	0.6	0.9	1.8	1.2	0.3
PASIR RIS	86.2	7.1	1.5	1.2	0.9	2.2	0.3
PUNGGOL	86.9	7.9	0.3	0.3	1.8	1.7	0.8
QUEENSTOWN	83.5	9.0	0.4	0.2	2.9	2.0	0.8
RIVER VALLEY	60.0	6.3			15.8	3.2	2.1
ROCHOR	90.4	3.8		1.4	2.4	1.9	
SEMBAWANG	77.2	14.6	0.3	0.5	0.6	3.6	1.0
SENGKANG	86.1	10.5		0.5	0.6	1.7	0.2
SERANGOON	86.2	7.0	0.4	0.2	2.2	2.4	0.8
SINGAPORE RIVER					60.0		
TAMPINES	86.4	8.9	0.5		0.9	2.1	0.7
TANGLIN	76.3	7.9			5.8	7.2	2.9
TOA PAYOH	88.3	7.0	0.5	0.2	1.0	1.8	0.5
WOODLANDS	83.0	11.7	0.3	0.7	0.5	2.5	0.2
YISHUN	82.5	12.7	0.9	0.3	1.0	1.6	0.5

Table A5
Recollection Bias by Individual Characteristics

The table shows the recollection bias across different individual characteristics. The recollection bias is the percentage difference in reported travel time between the passenger and driver of car, van, truck, or motorcycle. The driver and passenger are from the same household, travel on the same day, and start the trip from the same location.

	2012			2008		
	Obs	Mean	P-value	Obs	Mean	P-value
Armed forces	47	0.2%	0.16	57	2.2%	0.11
Associate professional & technician	154	2.5%	0.00	512	3.5%	0.00
Cleaner, labourer & related worker	20	10.3%	0.13	44	3.5%	0.16
Clerical worker	234	2.4%	0.00	257	6.2%	0.00
Legislator, senior official & manager	689	3.1%	0.00	497	4.6%	0.00
Plant & machine operator & assembler	25	1.8%	0.10	50	7.4%	0.07
Production craftsman & related worker	28	5.2%	0.17	113	3.7%	0.01
Professional	1148	3.2%	0.00	1479	3.2%	0.00
Self Employed / Businessman	25	0.6%	0.16			
Service & sales worker	443	1.6%	0.00	599	3.5%	0.00
Others				86	8.9%	0.00
$1-$1000	88	5.5%	0.01	171	2.9%	0.02
$1001-$1499	29	4.5%	0.02	58	3.1%	0.01
$1500-$1999	95	1.7%	0.00	208	5.3%	0.00
$2000-$2499	207	2.3%	0.00	293	2.9%	0.00
$2500-$2999	172	1.5%	0.00	327	4.5%	0.00
$3000-$3999	299	1.8%	0.00	531	5.1%	0.00
$4000-$4999	282	2.9%	0.00	398	5.0%	0.00
$5000-$5999	246	2.9%	0.00	304	2.9%	0.00
$6000-$6999	76	5.3%	0.02	145	2.7%	0.01
$7000-$7999	56	3.3%	0.03	106	2.8%	0.03
$8000 and above	248	3.1%	0.00	399	4.2%	0.00
No Income	1977	2.8%	0.00	2835	3.8%	0.00
Refused	1074	3.2%	0.00	887	2.8%	0.00
Female	2396	2.5%	0.00	3382	3.4%	0.00
Male	2453	3.2%	0.00	3280	4.2%	0.00
6-9 yrs old	364	2.9%	0.00	765	4.4%	0.00
10-14 yrs old	493	3.4%	0.00	691	3.9%	0.00
15-19 yrs old	312	5.0%	0.00	369	4.7%	0.00
20-24 yrs old	83	3.6%	0.00	108	3.5%	0.02
25-29 yrs old	155	1.8%	0.00	226	2.2%	0.02
30-34 yrs old	417	2.5%	0.00	523	2.7%	0.00
35-39 yrs old	553	1.6%	0.00	861	3.7%	0.00
40-44 yrs old	601	3.1%	0.00	918	3.2%	0.00
45-49 yrs old	608	3.2%	0.00	754	5.0%	0.00
50-54 yrs old	434	3.6%	0.00	608	4.7%	0.00
55-59 yrs old	286	2.1%	0.00	343	4.4%	0.00
60-64 yrs old	229	2.2%	0.00	221	2.1%	0.00
65-69 yrs old	154	2.5%	0.00	116	2.5%	0.01
70-74 yrs old	80	1.7%	0.05	88	2.5%	0.05
75-79 yrs old	51	0.4%	0.32	40	0.6%	0.32
Chinese	4091	2.9%	0.00	5645	3.8%	0.00
Indian	392	4.1%	0.00	361	4.4%	0.00
Malay	271	0.9%	0.00	442	4.5%	0.00
Others	95	2.4%	0.01	214	2.9%	0.00
Permanent Resident	298	3.5%	0.00			
Singapore Citizen	4452	2.9%	0.00			
Work Permit(Foreign Domestic Workers)	43	0.7%	0.32			

Figure A1
Map of Industrial Areas in Singapore