Impact of Electronic Road Pricing (ERP) Changes on Transport Modal Choice#

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Date: March 29, 2015

Revised: July 8, 2015

 # We would like to thank the Land Transport Authority (LTA) for sharing the public transportation use data used in this study.

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ABSTRACT

This paper analyzes the effect of congestion toll rate change on the change of commuters' transport modal choice in Singapore's context. Amongst several alternatives that commuters can choose when they face increase of congestion tax, this study specifically tests the impact on the modal change to public bus transportation. This study finds that commuters switch to public bus services by 12 per cent to 20 per cent in the morning hours and by approximately 10% in the evening after congestion tax increase in the affected gantry area compared to the non-affected area and time through difference-in-difference method. Also, we found that the increase in bus ridership has long-lived effect at least within two months. Time falsification found no significant modal change. Other confounding factors from macro-economic standpoint and service quality couldn't explain the results as the modal change occurred in short period within specific area and time.

Keyword: *Congestion Charge; Traffic Management; Electric Road Pricing (ERP); Transport Modal Choice*

JEL Code: D1, H2, R4, R5

Electronic copy available at: http://ssrn.com/abstract=2641270

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1. Introduction

It is known that traffic congestion incurs social deadweight cost (Foster, 1974; De Borger and Proost, 2001; Lomax and Shrank, 2005). Tennøy (2010) suggested a few ways to reduce urban traffic volumes. The first is to encourage efficient land development that requires less traffic. Second is to impose physical and fiscal restrictions, which include road pricing, parking regulation, or traffic regulations. Third is to improve the social infrastructure to provide better environment for public transportation, walking, or cycling. Fosgerau and Palma (2013) found that parking fees appeared to be easy to carry out with less political conflict. Parking fee policy is even more effective when fee is time-varying or combined with early bird specials. This paper focuses on the effect of the second policy, especially on the road pricing. Road pricing has been adopted in many countries including Singapore, Sweden, UK, etc. Gopinath and Sarath (2010) finds that Singapore's road pricing system reduced 20-30% of the downtown passenger car traffic and Stockholm's traffic volume decreased by at least 20%. In the same paper, the authors showed several options for drivers to avoid congestion tax. Drivers can a) pay ERP charge; b) change the time or route of the journey to pay less or to avoid ERP charge; c) switch to a public transportation; d) modify destination or give up the trip. Ubbels and Verhoef (2005) added a few more options to those introduced by Gopinath and Sarath (2010). They added change in vehicle occupancy, change in driving style, class choice (for public transport), etc.

The effect of road pricing or congestion tax has been long studied in the transport policy area. In a sense, the transport policy seems to benefit drivers. Palma et al. (2006) found that users, especially in the cases of 4 European cities including Paris, Brussels, Oslo and Helsinki, could get sizable amount of benefit from commuting time reduction, cost saving in vehicle management, or enhanced quality of public transportation when road pricing was introduced in each country. However, it doesn't always appear to be the case. Just like other policies, there were countries where the effort to curb down the traffic volume didn't turn out to be success. Indirect assessment of transport policy was conducted in Mexico City and Santiago by Gallego et al. (2013) . This paper tested the effects of two separate transport policies in both countries. Both countries were suffering from severe air pollution from the car traffic. The governments introduced policy measures to retire old public transportation and restrict car use. However the result of the study showed that both policies were not successful, especially in long-term, to control the traffic level by monitoring CO level. Instead of lower level of CO after the implementation of the policy, the authors found that the CO level and commuting hours in both cities increased in the long-term. Percoco (2014) studied a unique transport policy to restrict the vehicle inflow to the CBD in Milan, Italy. In 2008, the city started to charge €2-€10 depending on the cars' engine emissions standard. This policy was successful in controlling the number of less fuel-efficient vehicle in the CBD, while it failed to restrict total traffic volume in the CBD as more of toll-exempt vehicles that use liquefied petroleum gas or bi-fuel and toll-exempt hybrid vehicles entered CBD area.

While all the existing studies examine the magnitude of change in car use, it is hardly known how the commuters change their transportation modal choice. It has been proved that the drivers show responses to the transport policies. From the perspective of policy makers, it would be much better if drivers change their transportation mode from self-driving to eco-friendly mode, such as cycling, or public transportation. Instead of natural experiment research, a few papers conducted surveys. According to the survey result of Ubbels and Verhoef (2005) in the Netherlands, switching to public transportation ranked as the second highest[1] response to hypothetical implementation of peak and off peak kilometer charge. Similar survey was conducted in New Zealand and the result of O'Fallon et al. (2004) found that the 21 percent of survey respondents were willing to choose to walk and to use public transportation, while 67% insisted that they would still drive cars when congestion tax were to be introduced. The survey of Hu and Saleh (2005) found that almost 37% of car users were willing to spend less or change the shopping destination if they had been asked to pay congestion tax for their shopping trip to the CBD. As aforementioned, all the extant studies found the effect of the transportation policy in the car use or air pollution levels after introducing policies or through hypothetical surveys. However, the results from survey has limitation in that it is just hypothetical answers that are not always connected to actual behavioral change. As it is eminent that the demand for road during the commuting hours, especially in the morning peak hours, is quite static, the increase of the public transportation ridership can be interpreted as the decrease of self-driving modal choice. With this assumption, this paper tested real change of modal choice after the toll increase through

[1] The highest response was to travel at other times (47.7%). 17.6% of respondents answered that they would use public transport when toll is levied.

natural experiment in Singapore.

Singapore has been known as one of the countries with most efficient road pricing system. Singapore implemented road pricing system in 1975 with the name of Area License Scheme and started to collect toll electronically from 1998 by having all the vehicles equipped with car transponder, which is called In-vehicle Unit or IU, where preloaded cash cards are inserted. Total number of gantries[2] was 45 in 2004 and it amounted to 71 in 2013. After quarterly traffic speed review, the Land Transport Authority (LTA) adjusts the toll rate by the incremental of S$0.50 or S$1.00. This paper studies the effect of toll increase, which was announced on July 29th, 2013, on the commuters' transportation modal choice. Especially we closely test the change of public bus use around the gantries that went through toll increase after the toll adjustment compared to the other areas before the increase by using difference-in-difference method. The LTA announced that it would increase toll rate by S$1.00 for 6 gantries and S$0.50 for 1 gantry. 6 of them were affected during the morning peak hours and only 1 gantry had toll increase in the evening peak hours with effective date of August 5th, 2013[3]. Due to small number of bus lines that operate in the southern area, where two of the gantries were affected in the morning hours, this paper focuses only on the five gantries in the central and northern area of Singapore during morning and evening peak hours. Our dataset contains all the bus card use information, including boarding time, alighting time, travelling distance, bus number, direction, etc. We set the treatment area by drawing 1 km radius circle around the affected gantries and sorted all the bus numbers that stop at the bus stops within the 1 km circle. We set a control area that doesn't overlap with the treatment area in the same manner to get the bus numbers. By using diff-in-diff method, we compared the bus ride numbers of the treatment area to those of control area before and after the toll increase. As the dataset starts from 1st of August, 2013, our control period constitutes 4 days and treatment period ends at the end of September 2015. To test the heterogeneous responsiveness in time, we tested two different treatment period: one with August data and the other with August and September.

Our study contributes in a few ways. First of all, we test the empirical responsiveness

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[2] Gantry means a structure that looks like overhead bridge. Electronic sensors are installed on gantries and toll amount is deducted when cars pass under gantries. For more details, please see Appendix 2 and Appendix 3.

[3] For more detail, see Appendix 1.

to the change of road pricing with natural experiment. Even if there were a few studies that conducted tests on the effect of new implementation of road pricing, our paper is the first paper that studied the toll increase after implementation. Secondly, we show the varied responsiveness over time and during the day. This test enabled us to figure out the magnitude of response in the morning and in the evening, when the demand for road is quite inelastic with respect to road pricing. (Ferrari, 2010) By applying our findings to the real policy scheme, each government can establish more effective and efficient traffic control system. Thus, policy implication of this study is clear. Thirdly, we can test if the electronic road pricing system in Singapore is salient enough to affect the commuters' modal choice. Finkelstein (2009) argues that adopting electronic road pricing system makes tolling system less salient and drivers pay less attention to the toll increase compared to the case of manual toll collection.

To preview the result, we found that the commuters responded to the toll rate increase during our study window. Especially, the commuters in the morning peak hours showed greater responsiveness compared to the evening peak hours. This seems to be the phenomenon caused by more inelastic demand for road in the morning than in the evening. Also, we found that the positive increase of bus ride after the toll increase in the treated area doesn't revert to its previous level in short-term, at least in two months. Thus, we show that toll increase has long-lived effect on the transportation modal choice amongst commuters. When we test the effect of arbitrary toll increase hours during the same study window as a robustness test, we found insignificant results throughout all the model specifications.

This paper is organized as follows. Section 2 and 3 discuss the road pricing system in Singapore and the data/methodology respectively. Section 4 documents the responsiveness of commuters to the toll increase and results from additional robustness tests, and Section 5 concludes.

2. Urban Road Pricing in Singapore

Singapore is a small island-country with its size of 716.1 square kilometers and connected to Malaysia via two links. Singapore's government implemented road pricing scheme in 1975 to alleviate the congestion level. In the beginning, the toll was charged only within Central Business District under Area Licensing Scheme (ALS). In 1998, electronic road pricing (ERP) system was introduced to have more efficient toll collection system and easier addition of charging areas. The charging zone expanded over time and total number of gantries in Singapore increased from 33 when it was first implemented to 71 in 2013.

LTA periodically monitors traffic speed and revises the toll rate. Desired speed for CBD area is 20 to 30 kilometer per hour for ordinary roads and 45-65 kilometer per hour for expressways. If the 85 percentile speed during the past quarter falls below the lower limit, LTA increases the toll rate, while the speed is over the higher limit LTA lowers or abolish the existing toll rate. This means that only traffic speed is the factor that affect the toll rate change. The change of toll rate is announce at least one week before the effective date. All the toll rates for each vehicle type are shown on the gantries during the charging hours to increase the salience to the drivers. Toll is charged dynamically depending on 30-minute slot and area. The minimum charge is S$0.50 and the maximum is S$6.00 as of May 4th, 2015. As the toll is charged per each entry to the charging area, drivers may have to pay multiple times depending on the travelling route. ERP charges are deducted automatically from pre-loaded cash-card. All the vehicles registered in Singapore are required to be equipped with transponder called In-vehicle Unit (IU) where cash card is inserted. Appendix 2 and Appendix 3 explain more in detail regarding the way how the ERP system in Singapore works.

On July 29th of 2013, LTA announced that it would increase toll rate by S$0.50 or S$1.00 for four gantries along southbound CTE after Braddell Road and PIE Slip Road into southbound CTE (4 gantries in the morning peak hours), one gantry along northbound CTE before PIE (evening peak hours), and two gantries along ECP and KPE Slip Road onto ECP (morning peak hours)[4]. The revised toll rate was effective from August 5th, 2013. CTE southbound gantries were affected from 7:00 am to 8:00 am and CTE northbound gantry was affected from 5:30 pm to 6:30 pm. However, this doesn’t mean that these gantries are free of charge during other time slots. Tolling system of CTE southbound gantries were operating from 7:00 am to 9:30 am and CTE northbound gantry was charging toll from 5:30 pm to 8:00 pm with previously announced rate during our study period.

3. Data and Empirical Methodology

[4] CTE, KPE, and ECP stand for Central Expressway, Kallang-Paya Lebar Expressway, and East Coast Parkway respectively.

3.1. Data

The dataset used in this study contains information of bus card use in Singapore from August 1st, 2013 to September 29th, 2013. The dataset contains information about bus number, boarding station, alighting station, travelling distance, boarding time, alighting time, bus card ID, and passenger type. As this study seeks to see the responsiveness of the commuters to the toll rate increase, we drew 1 km radius circle around the affected gantries and demarcated treatment area. We also set control area around gantries which were not affected by the toll increase on August 5th, 2013 and which had least number of bus lines that were operating in the treatment area. The geographical location of treatment area and control area is shown in Fig 1.

[Insert Figure 1 here]

We kept bus trip information from the bus lines that went through the 1 km radius treatment and control area from the main dataset. Additionally, as the control period before the toll increase contains only 4 days, which range from Thursday to Sunday, we trimmed the dataset to contain only Thursday, Friday, Saturday, and Sunday. This is to avoid the potential issues stemming from the varied number of bus ridership per each day of week between treatment period and control period. We also dropped feeder bus lines, which covers small area in each neighborhood and express buses that operate only during the peak hours for designated specific areas. The longest bus route in Singapore is 38.8 km. If total ride distance is over 38.8 km, we dropped these trips from our sample as these trips are supposed to be data error or abnormal trip behavior such as a city tour with round trips. Additionally, if bus riders forget to tap out bus card when they alight, the maximum charges are to be deducted from the cash card balance. By dropping all the bus trip information over 38.8 km, we could remove these data errors. Thus, we used 37,612,252 bus ride information for 77 bus lines. Average ride time was 15.37 minutes and average ride distance was 4.6 km.

We used geocode of each bus stops and location of ERP gantries in the treatment area and control area. By using the exact location of gantries, we drew 1 km radius circle around each gantry. Then, all the bus stations within the circles were selected to see what bus lines pass through the gantry area. This process enabled us to match bus ride information with the treatment and control area.

3.2. Empirical Methodology

In our "diff-in-diff" format, we generated a "Treatment" dummy variable that has a value of 1 if bus line is passing through treatment area and southbound direction or northbound direction in the morning peak hours and evening peak hours respectively; and 0 otherwise for the control samples. This "Treatment" indicator segregate bus lines that were more likely to carry the commuters who were affected by the toll increase from the other bus lines in the control area where toll increase didn't play any roles. Regarding the second difference, we defined two separate variables: "$\text{After}_{\text{affected}}$" and "$\text{After}_{\text{peak}}$". $\text{After}_{\text{affected}}$ is 1 when the trip is after 5th of August, 2013 and boarding time falls on the time slot when the toll rate increased; and 0 otherwise. $\text{After}_{\text{peak}}$ is defined as trips that happened after August 5th, 2013 and within total peak hours when previous toll rate is charged. The purpose of this separation is to see the effect of toll increase on the shift of travelling time to earlier or later time slot. It is highly likely that commuters adjust their departure time when they switch to public transportation due to the different commuting duration per each transportation modal choice.

Our dependent variable is log-normalized total number of bus ride per each bus line and each 30-minute slot of each day. We also added an interaction term "Treatment X $\text{After}_{\text{afffected}}$" and "Treatment X $\text{After}_{\text{peak}}$" in separate test. The coefficients of our interest is those of interaction terms. The coefficient will tell us to what extent the treated area during the treated time responded to the toll increase compared to the control area and time where there was no toll increase. The model specification is written below:

$$\ln(Number\ of\ Ride_{i,t}) = \alpha + \beta_1(Treatment \times After_{affected}) + \beta_2(Treatment) + \beta_3(After_{affected}) + \gamma_i + \textstyle\sum_1^3 \delta_d + \varepsilon_{i,t} \qquad \text{Eq (1)}$$

where i and t stand for each bus line and 30-minute slot of each day respectively; α is a constant term; β_1 is a coefficient on the interactive term, which will tell us the effect of the toll adjustment; β_2 is a coefficient for treatment area, which identifies bus rides that pass through the 1 km radius area around treated gantries; β_3 is a coefficient for treatment time; γ_i is a bus line (77 bus lines in the sample) fixed effect; δ_d is a day of week fixed effect and

$\varepsilon_{i,t}$ is an error term. In Equation (1), the coefficient β_1 captures the comparative responsiveness of treated area during the treated time compared to the control area and control time. Equation (1) was replicated to test the responsiveness during the whole peak hours by replacing $After_{affected}$ with $After_{peak}$ in the empirical test. Tests based on Equation (1) was repeated for CTE southbound data and CTE northbound data respectively. We expanded Equation (1) by adding two more time indicator variables that captures the effect of public holiday and school terms in separate tests[5]. The extended model specification is written below:

$$\ln(Number\ of\ Ride_{i,t}) = \alpha + \beta_1(Treatment \times After_{affected}) + \beta_2(Treatment) + \beta_3(After_{affected}) + \gamma_i + \sum_1^3 \delta_d + D_{school} + D_{holiday} + \varepsilon_{i,t} \quad \text{Eq (2)}$$

More detailed description of all the variables are listed in Table 1 below.

[Insert Table 1 here]

4. Empirical Results

We show the results from Eq (1) and Eq (2) with a few variations in specification. To test if the effect of the toll increase lasts for longer period or not, we tested one-month window and two-month window separately. It is likely that commuters revert back to previous transportation mode after a few weeks. However, if the effect of toll increase was big and salient enough, we should not see any drop in the interaction terms of Eq (1) and Eq (2). The difference in responsiveness between morning affected (or peak) hours and evening affected (or peak) hours was tested by comparing CTE Southbound and CTE Northbound specification as CTE Southbound experienced toll increase in the morning while Northbound faced toll increase in the evening. Following the main results in both one-month and two-month window test, we tested if the responsiveness was still significant during falsified peak hours, which was arbitrarily set between 2:00 pm and 3:00 pm during the test period. All the empirical tests include bus number fixed effect and day of week fixed effect.

4.1. One-Month Window Tests

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5 August 8th and 9th were Hari Raya Puasa (Islamic holiday) and National Day in Singapore. Most of universities is Singapore started new semester on August 12th.

Table 2 shows the result from Eq (1) within one month test window. Through this test we found positive response from the commuters during the hours when the toll increased. CTE Southbound had toll increase from 7:00 am to 8:00 am with effective date of August 5th, 2013, while CTE Northbound experienced toll increase from 5:30 pm to 6:30 pm. First panel on the left shows the result of CTE Southbound in the morning hours. Dependent variable is log-bus ridership per each 30 minutes just as explained in Eq (1). The coefficient of interactive term is of our interest. The coefficient of interaction term indicates the degree of commuters' responsiveness to the toll increase in the treated area compared to the control group. We found that the number of bus ride in the area after the toll adjustment increased by 11.8% compared to the control group without toll increase. The responsiveness is stable at 11.8% throughout different specification of the test model with or without school term dummy or holiday dummy. We added two separate dummy for national holiday and for a period of school term. Column (2) contains both dummies of holiday and school, while column (3) and (4) has only one of the two dummies. Adding holiday dummy or school dummy didn't change the coefficient of interaction term, while R-squared value increased slightly. Thus, this confirms that our results were not affected by neither national holiday nor school term. Second panel is the result from the evening hours in the CTE Northbound traffic. It is natural to guess that the demand for road in the evening is less inelastic than in the morning as people finish their work in different hours. Additionally, people might spend some time in the city after work or head to other destination. So, we expected that we would see less concentration of traffic in the evening peak hours. Second panel of Table 2 confirmed our expectation. The interaction term is economically significant at around 7% but statistically insignificant. Compared to the magnitude of coefficients in morning hours, the responsiveness in the evening hours is smaller and less significant. However, the R-squared value is higher than that of CTE Southbound. Adding holiday dummy and school dummy didn't affect the magnitude of the responsiveness in column (6), (7), and (8).

[Insert Table 2 here]

In Table 3, we tried to find dispersion of departure time. As Gopinath and Sarath (2010) argued, commuters can switch to public transportation to avoid road pricing. However, the duration of commuting shall change after switching to public transportation. Accordingly, it is likely that commuters choose different departure time when they switch transportation modal choice from self-driving to public transportation. So, we replaced $\text{After}_{\text{affected}}$, where the effect on the time slots with toll increase was captured, with $\text{After}_{\text{peak}}$ to test total effect during the morning and evening peak hours. CTE Southbound had peak hours from 7:00 am to 9:30 am, while the peak hours of CTE Northbound ranged from 5:30 pm to 8:00 pm. It should be noted that during the total peak hours the commuters had to pay the toll at the previous toll level except for the affected hours where additional toll was added to the previous toll rate as of August 5th, 2013. The magnitude of response from morning peak hours almost doubled when the treatment time was expanded to whole peak hours. In addition to that, we found that the coefficient of CTE Northbound became statistically significant and more meaningful economically. This makes sense in that most of workers don't finish work at fixed schedule. On the other hand, most of workers are expected to be stickler for punctuality in the morning. So, it is natural to find higher and more significant response in the morning hours than evening hours. Similar to Table 2, holiday dummy and school term dummy didn't affect the result significantly.

[Insert Table 3 here]

4.2. *Extended Period Test: Two-Month Window Tests*

We conducted the same test with extended window. In Table 2 and Table 3, total sample period was limited to August, 2013. In Table 4 and Table 5, total test period includes both August and September of 2013. This is to see if the responsiveness reverts back to previous level before the implementation of toll increase or if toll increase has long-lived effect on the transportation modal choice. Finkelstein (2009) stated that drivers are less sensitive to toll increase when the toll is collected electronically. Even if we found positive increase of bus ridership in one-month window, the effect of toll increase might revert to its old state when the toll increase was not huge enough or the toll incremental was not salient enough, especially with electronic road pricing system.

In Table 4, we found that there was slight increase of response both in CTE Southbound and CTE Northbound in 2-month window compared to 1-month window. The interactive terms in Table 4 increased by approximately 2.3% and 1% in the morning affected hours and in the evening affected hours respectively. This means more commuters switched from self-driving mode to public bus ride mode over time. Even if the incremental is not dramatically high, the results confirms that toll increase had long-lived effect on the modal choice at least within 2-month window. Additionally, the coefficients of CTE Northbound test became statistically significant. Holiday dummy and school term dummy didn't affect the result in the 2-month window, either. This result lend further support to the notion that the ERP policy in Singapore is effective in inducing commuters to use more public transportation mode both in 1-month and 2-month window.

[Insert Table 4 here]

We also tested the model of peak hours with extended two-month period. The result lend credence to our finding in Table 4. The magnitude of responsiveness increased by 3% and 2% in CTE Southbound and CTE Northbound respectively. Thus, we can conclude that the impact of toll increase on the modal choice doesn't get alleviated at lease in two months. Additionally, we found the same trend of comparison between affected hours and peak hours as we did in Table 2 and Table 3. We found significant increase of responsiveness when we expanded the test window to the total peak hours. Thus, the results from two-month window reconfirm that more commuters adjusted their departure time in longer term, too.

[Insert Table 5 here]

4.3. Falsification Test

We conduct a time falsification test to double-check if the positive increase in number of bus ride is unique phenomena in the specified treatment time and treatment group. If we find similar significant increase of ridership in the falsified hours, the main result can be nullified. To see this, we arbitrarily set the toll increase hours to 1 hour slot from 2:00 pm to 3:00 pm with the same 1-month and 2-month window. Following the model specification of Table 2-Table 5, we tested two separate period of one month and two months from August 2013.

The coefficients of interaction terms in Table 6 (1-month window) and Table 7 (2-month window) are neither economically significant nor statistically significant. Especially, The responses from CTE Southbound in one and two-month window and CTE Northbound in one-month window were negative. Especially, it is notable that the coefficients in column (45)-column (48) are economically not different from zero. After considering all the results from Table 6 and Table 7, we confirm that the positive increase in number of bus ride is only seen in our treatment group and treatment time. Thus, the positive increase of bus ridership after the toll increase in the treated area is a unique phenomenon which can be seen only in the peak hours.

[Insert Table 6 here]

[Insert Table 7 here]

4.4. Potential Confounders

Any unobserved confounders might have had effects on the commuters' modal choice in the treatment group and treatment time. Paulley et al. (2006) argued that fares, quality of service, income and car ownership can affect the demand for public transportation. Amongst all those factors, only the fare can change the demand for bus during our study period as the total sample period is too short to be affected by macro-economic factors. However, fare change cannot have affected our result as there was no fare change during our study period and this was confirmed by the LTA. At the same time, it is hard to believe that there was change of service quality throughout the sample area during the test period. Even if there had been enhancement of service quality, it is impossible that commuters get induced to use more buses right after the ERP rate increase coincidentally. It should be also noted that there are only two bus operators[6] in Singapore. One operates 102 bus lines and the other operated 250 lines. Both operators are not limited to geographic regions despite different company size. Kingham et al. (2001) shows that the drivers are likely to use public bus services if there are more frequent services, better drop-off sites, discount tickets, etc. There were no known change of bus schedules, general increase/improvement of bus stops, or change of concession card scheme during our study period. Even if the macro-economic factor cannot affect the commuters' behavior in short term, a sudden increase of unemployment rate might induce modal change. We checked the unemployment rate from 2012 to 2014. Total resident unemployment rate in 2012 was between 2.7% and 2.9%. Unemployment rate ranged from

[6] The two companies are SMRT and SBS Transit.

2.7% and 2.9% in 2013. From the figures of Table 8, we found no significant change of unemployment rate between 2012 and 2013. Additionally, Table 9 shows that the median gross monthly income from work of full-time employed residents increased in 2013 compared to 2011 and 2012. Thus, we can conclude that general commuters in Singapore didn't experience financial hardship in 2013.

[Insert Table 8 here]

[Insert Table 9 here]

5. Conclusion

Since the first introduction of road pricing, congestion tax has been advocated by many scholars and considered in many countries. Many papers have shown the effectiveness of road pricing and expected transportation modal change through a series of surveys. However, the actual modal shift has been hardly studied in urban studies. In August of 2013, Singapore's government increased toll rate for 7 gantries during sub-slots of peak hours. This paper aims to see the commuters' modal change after the toll increase. We defined treatment group as the bus trips of bus numbers that operated through 1 kilometer radius around the affected gantries both in the morning and evening hours. Two separate treatment time were also designed to segregate the trip hours. First is affected hours when the new toll increases were applied. The other is total peak hours when toll was charged at previous level without further toll adjustment in August 2013. Two other gantries were selected as control area where the toll increase of August 2013 was not applied. By using difference-in-difference method, we found that there were significant increase of bus ridership both in the morning hours and evening hours. The magnitude of the increase in bus ridership during the morning hours ranged from 12% to 20% from the affected hours and total peak hours respectively within one month after the increase, while the increase during the evening hours were significant only during the peak hours by 10%. This lower responsiveness in the evening seems to be due to the relatively flexible trip schedule of commuters in the evening compared to the morning hours. When we extended the treatment period to two-month window, we found slight increase of the responsiveness with no decrease of bus ridership. This confirms that the effect of toll increase had long-lived effect on the increase of bus ridership at least in two months. A separate time falsification test was conducted by setting falsified treatment time slot from 2:00 pm to 3:00 pm within the same treatment area. No significant response was found in the falsified treatment time and some of the coefficients were not economically different from zero. The results of this paper confirms the survey response of the extant papers and adds significant contribution to the policy measures. Additionally, this paper is the first to test the actual response in transportation modal change to public transportation with natural experiment. A few confounders to the results of this study can be considered from the factors described in the existing papers. However, it is hard to connect macro-economic factors with the main results of this paper as it is less convincing that macro-economic factors affected in the specific area and time, especially within one or two months' short period. This paper can be extended to other transportation modal choice, such as cycling, subway, etc., with feasible study framework and reliable datasets. If the future study on other transportation modal choice finds significant results, it will be more meaningful to the policy makers along with current paper.

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Table 1: List of Variables and Descriptions

Variables	Description
lride	Number of bus ride of each bus line per 30 minutes in logarithm term
Treatment	A location identification variable that has a value of 1, if bus number of the ride passes through 1 km radius circle around gantries with toll increase on August 5th, 2013; and 0 otherwise
$After_{affected}$	A time dummy variable that identifies the policy shocks, and it has a value of 1, if a bus trip started on and after August 5th, 2013 within the toll-increased hours; and 0 otherwise
$After_{peak}$	A time dummy variable that identifies the policy shocks, and it has a value of 1, if a bus trip started on and after August 5th, 2013 within the peak hours; and 0 otherwise
$After_{falsify}$	A time dummy variable that identifies the policy shocks, and it has a value of 1, if a bus trip started on and after August 5th, 2013 within the falsified affected hours (2:00pm-3:00pm); and 0 otherwise
Treatment × $After_{affected}$	An interaction dummy variable is used in the diff-in-diff model to test the joint effects of ex-post increase of ERP rate for the number of bus ride after August 5th, 2103 within affected hours
Treatment × $After_{peak}$	An interaction dummy variable is used in the diff-in-diff model to test the joint effects of ex-post increase of ERP rate for the number of bus ride after August 5th, 2103 within total peak hours
Treatment × $After_{falsify}$	An interaction dummy variable is used in the diff-in-diff model to test the joint effects of ex-post increase of ERP rate for the number of bus ride after August 5th, 2103 within arbitrary toll charging hours(2:00pm to 3:00pm)
$D_{holiday}$	A dummy variable for the public holiday on August 8th(Hari Raya Puasa) and August 9th (National Day) of 2013; and 0 otherwise
D_{school}	A dummy variable for the school term (after August 12th, 2103) when most of universities start new semester in Singapore; and 0 otherwise

Note: The table summarizes a list of variables with their descriptions. lride, which is the log-number of bus ride during each 30-minute slot, is used as the dependent variable in the model. We compute the lride for each bus number during the test window. Other variables are used as independent variables in the empirical models.

Table 2: Effects of Toll Increase on Bus Ride during Affected Hours within 1 Month

	Test Period: August 1st 2013-August 25th 2013							
	CTE Southbound				CTE Northbound			
Dependent variable=lride	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment X $After_{affected}$	0.118**	0.118**	0.118**	0.118**	0.070	0.068	0.069	0.068
	(2.23)	(2.25)	(2.23)	(2.25)	(0.99)	(0.97)	(0.99)	(0.97)
Treatment	0.005	0.005	0.005	0.005	0.011	0.011	0.011	0.011
	(0.49)	(0.54)	(0.50)	(0.54)	(0.88)	(0.87)	(0.87)	(0.87)
$After_{affected}$	0.255***	0.296***	0.238***	0.292***	0.633***	0.677***	0.616***	0.670***
	(8.19)	(9.59)	(7.64)	(9.47)	(17.40)	(18.83)	(16.95)	(18.69)
Constant	5.158***	5.167***	5.110***	5.158***	5.768***	5.781***	5.722***	5.767***
	(206.25)	(206.86)	(202.67)	(208.95)	(164.98)	(166.20)	(162.66)	(167.32)
Observations	57,071	57,071	57,071	57,071	37,506	37,506	37,506	37,506
R-squared	0.304	0.322	0.307	0.322	0.337	0.356	0.339	0.356
Bus # FE	YES	YES	YES	YES	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES	YES	YES	YES	YES
$D_{holiday}$	NO	YES	NO	YES	NO	YES	NO	YES
D_{school}	NO	YES	YES	NO	NO	YES	YES	NO

*Note: This table reports the result of regressing log-bus ridership on the interaction dummy variable "Treatment $\times$ $After_{affected}$" where Treatment means all the bus rides in the 1 kilometer radius around the gantries that experienced toll increase in August 2013 and $After_{affected}$ is indicator dummy for the affected hours and one month after the effective toll increase date. The coefficients on the interactive terms capture the effects of the ex post increase of toll on the change of the bus ridership in the affected areas and hours relative to the control group. Each column was teste with or without indicator dummy for public holiday and for university semester. Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 3: Effects of Toll Increase on Bus Ride during Peak Hours within 1 Month

	Test Period: August 1st 2013-August 25th 2013							
	CTE Southbound				CTE Northbound			
Dependent variable=lride	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treatment X $After_{peak}$	0.200***	0.199***	0.199***	0.199***	0.105**	0.103**	0.105**	0.102**
	(5.88)	(5.93)	(5.87)	(5.92)	(2.34)	(2.32)	(2.33)	(2.31)
Treatment	-0.003	-0.003	-0.003	-0.003	0.007	0.007	0.007	0.007
	(-0.32)	(-0.28)	(-0.31)	(-0.28)	(0.56)	(0.56)	(0.56)	(0.55)
$After_{peak}$	0.264***	0.312***	0.247***	0.304***	0.541***	0.595***	0.526***	0.583***
	(13.08)	(15.55)	(12.23)	(15.24)	(22.95)	(25.44)	(22.26)	(25.08)
Constant	5.161***	5.176***	5.116***	5.161***	5.769***	5.790***	5.728***	5.768***
	(206.86)	(207.87)	(203.36)	(209.71)	(165.75)	(167.43)	(163.51)	(168.27)
Observations	57,071	57,071	57,071	57,071	37,506	37,506	37,506	37,506
R-squared	0.308	0.327	0.310	0.327	0.344	0.364	0.345	0.363
Bus # FE	YES	YES	YES	YES	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES	YES	YES	YES	YES
$D_{holiday}$	NO	YES	NO	YES	NO	YES	NO	YES
D_{school}	NO	YES	YES	NO	NO	YES	YES	NO

*Note: This table reports the result of regressing log-bus ridership on the interaction dummy variable "Treatment $\times$ $After_{peak}$" where Treatment means all the bus rides in the 1 kilometer radius around the gantries that experienced toll increase in August 2013 and $After_{peak}$ is indicator dummy for the total peak hours and one month after the effective toll increase date. The coefficients on the interactive terms capture the effects of the ex post increase of toll on the change of the bus ridership in the affected areas and during the peak hours relative to the control group. Each column was teste with or without indicator dummy for public holiday and for university semester. Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 4: Effects of Toll Increase on Bus Ride during Affected Hours within 2 Months

	Test Period: August 1st 2013-September 29th 2013							
	CTE Southbound				CTE Northbound			
Dependent variable=lride	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Treatment X $After_{affected}$	0.143***	0.143***	0.143***	0.143***	0.082*	0.081*	0.082*	0.081*
	(4.44)	(4.46)	(4.44)	(4.46)	(1.92)	(1.92)	(1.92)	(1.92)
Treatment	0.010*	0.010*	0.010*	0.010*	0.006	0.006	0.006	0.006
	(1.65)	(1.68)	(1.65)	(1.68)	(0.78)	(0.77)	(0.77)	(0.76)
$After_{affected}$	0.475***	0.483***	0.467***	0.480***	0.728***	0.738***	0.720***	0.734***
	(24.96)	(25.55)	(24.55)	(25.39)	(32.93)	(33.53)	(32.58)	(33.39)
Constant	5.186***	5.209***	5.126***	5.186***	5.767***	5.792***	5.707***	5.767***
	(310.90)	(301.01)	(297.37)	(312.67)	(248.25)	(242.69)	(239.44)	(249.77)
Observations	129,096	129,096	129,096	129,096	84,998	84,998	84,998	84,998
R-squared	0.307	0.315	0.308	0.315	0.338	0.346	0.339	0.346
Bus # FE	YES	YES	YES	YES	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES	YES	YES	YES	YES
$D_{holiday}$	NO	YES	NO	YES	NO	YES	NO	YES
D_{school}	NO	YES	YES	NO	NO	YES	YES	NO

*Note: This table reports the result of regressing log-bus ridership on the interaction dummy variable "Treatment × $After_{affected}$" where Treatment means all the bus rides in the 1 kilometer radius around the gantries that experienced toll increase in August 2013 and $After_{affected}$ is indicator dummy for the affected hours and two months after the effective toll increase date. The coefficients on the interactive terms capture the effects of the ex post increase of toll on the change of the bus ridership in the affected areas and hours relative to the control group. Each column was teste with or without indicator dummy for public holiday and for university semester. Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 5: Effects of Toll Increase on Bus Ride during Peak Hours within 2 Months

	Test Period: August 1st 2013-September 29th 2013							
	CTE Southbound				CTE Northbound			
Dependent variable=lride	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
Treatment X $After_{peak}$	0.234***	0.234***	0.234***	0.234***	0.121***	0.120***	0.120***	0.120***
	(11.34)	(11.40)	(11.34)	(11.39)	(4.43)	(4.42)	(4.42)	(4.42)
Treatment	-0.000	-0.000	-0.000	-0.000	0.001	0.001	0.001	0.001
	(-0.07)	(-0.04)	(-0.06)	(-0.05)	(0.14)	(0.12)	(0.13)	(0.12)
$After_{peak}$	0.467***	0.478***	0.459***	0.473***	0.637***	0.650***	0.630***	0.644***
	(37.82)	(38.93)	(37.21)	(38.54)	(44.31)	(45.38)	(43.77)	(45.03)
Constant	5.190***	5.225***	5.139***	5.190***	5.768***	5.807***	5.717***	5.768***
	(313.30)	(304.17)	(300.13)	(315.17)	(250.22)	(245.29)	(241.68)	(251.82)
Observations	129,096	129,096	129,096	129,096	84,998	84,998	84,998	84,998
R-squared	0.317	0.325	0.318	0.325	0.348	0.357	0.349	0.357
Bus # FE	YES	YES	YES	YES	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES	YES	YES	YES	YES
$D_{holiday}$	NO	YES	NO	YES	NO	YES	NO	YES
D_{school}	NO	YES	YES	NO	NO	YES	YES	NO

*Note: This table reports the result of regressing log-bus ridership on the interaction dummy variable "Treatment × $After_{peak}$" where Treatment means all the bus rides in the 1 kilometer radius around the gantries that experienced toll increase in August 2013 and $After_{peak}$ is indicator dummy for the total peak hours and two months after the effective toll increase date. The coefficients on the interactive terms capture the effects of the ex post increase of toll on the change of the bus ridership in the affected areas and during the peak hours relative to the control group. Each column was teste with or without indicator dummy for public holiday and for university semester. Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 6: Time Falsification Test with Arbitrary Event Time in 1 Month Window

	Test Period: August 1st 2013-August 25th 2013							
	Falsified Time (14:00-15:00)							
	CTE Southbound				CTE Northbound			
Dependent variable=lride	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
Treatment X $After_{falsify}$	-0.010	-0.012	-0.011	-0.012	-0.007	-0.010	-0.008	-0.010
	(-0.19)	(-0.23)	(-0.20)	(-0.23)	(-0.10)	(-0.14)	(-0.11)	(-0.14)
Treatment	0.007	0.008	0.007	0.008	0.012	0.012	0.012	0.012
	(0.77)	(0.82)	(0.78)	(0.82)	(1.00)	(0.99)	(0.99)	(0.99)
$After_{falsify}$	0.137***	0.177***	0.120***	0.174***	0.107***	0.148***	0.089**	0.145***
	(4.38)	(5.72)	(3.83)	(5.63)	(2.90)	(4.08)	(2.42)	(3.99)
Constant	5.157***	5.164***	5.108***	5.157***	5.768***	5.774***	5.718***	5.767***
	(206.01)	(206.50)	(202.41)	(208.67)	(164.05)	(164.97)	(161.68)	(166.26)
Observations	57,071	57,071	57,071	57,071	37,506	37,506	37,506	37,506
R-squared	0.303	0.321	0.305	0.321	0.330	0.348	0.332	0.348
Bus # FE	YES	YES	YES	YES	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES	YES	YES	YES	YES
$D_{holiday}$	NO	YES	NO	YES	NO	YES	NO	YES
D_{school}	NO	YES	YES	NO	NO	YES	YES	NO

*Note: This table reports the result of regressing log-bus ridership on the interaction dummy variable "Treatment $\times$ $After_{falsified}$" where Treatment means all the bus rides in the 1 kilometer radius around the gantries that experienced toll increase in August 2013 and $After_{falsified}$ is indicator dummy for the hours arbitrarily set (14:00-15:00) for falsification test and one month after the effective toll increase date. The coefficients on the interactive terms capture the effects of the ex post increase of toll on the change of the bus ridership in the affected areas and falsified hours relative to the control group. Each column was teste with or without indicator dummy for public holiday and for university semester. Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 7: Time Falsification Test with Arbitrary Event Time in 2 Months Window

	Test Period: August 1st 2013-September 29th 2013							
	Falsified Time (14:00-15:00)							
	CTE Southbound				CTE Northbound			
Dependent variable=lride	(41)	(42)	(43)	(44)	(45)	(46)	(47)	(48)
Treatment X $After_{falsify}$	-0.024	-0.025	-0.025	-0.025	0.004	0.003	0.004	0.003
	(-0.75)	(-0.78)	(-0.76)	(-0.78)	(0.10)	(0.07)	(0.09)	(0.07)
Treatment	0.014**	0.014**	0.014**	0.014**	0.008	0.008	0.008	0.008
	(2.29)	(2.33)	(2.29)	(2.32)	(1.00)	(0.99)	(0.99)	(0.98)
$After_{falsify}$	0.116***	0.124***	0.108***	0.122***	0.084***	0.092***	0.075***	0.090***
	(6.04)	(6.50)	(5.61)	(6.38)	(3.73)	(4.12)	(3.34)	(4.02)
Constant	5.185***	5.201***	5.120***	5.185***	5.767***	5.782***	5.699***	5.766***
	(309.47)	(299.23)	(295.79)	(311.20)	(246.02)	(240.03)	(237.03)	(247.47)
Observations	129,096	129,096	129,096	129,096	84,998	84,998	84,998	84,998
R-squared	0.301	0.309	0.302	0.309	0.326	0.334	0.327	0.334
Bus # FE	YES	YES	YES	YES	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES	YES	YES	YES	YES
$D_{holiday}$	NO	YES	NO	YES	NO	YES	NO	YES
D_{school}	NO	YES	YES	NO	NO	YES	YES	NO

*Note: This table reports the result of regressing log-bus ridership on the interaction dummy variable "Treatment × $After_{falsified}$" where Treatment means all the bus rides in the 1 kilometer radius around the gantries that experienced toll increase in August 2013 and $After_{falsified}$ is indicator dummy for the hours arbitrarily set (14:00-15:00) for falsification test and two months after the effective toll increase date. The coefficients on the interactive terms capture the effects of the ex post increase of toll on the change of the bus ridership in the affected areas and falsified hours relative to the control group. Each column was teste with or without indicator dummy for public holiday and for university semester. Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 8: Quarterly Unemployment Rate from 2012 to 2014

	2012	2013	2014
Resident Unemployment Rate (%)			
Annual Average	2.8	2.8	2.7
Seasonally Adjusted as at			
Mar	2.9	2.8	2.8
Jun	2.8	2.9	2.8
Sep	2.8	2.7	2.8
Dec	2.7	2.7	2.7

Source: Ministry of Manpower, Singapore

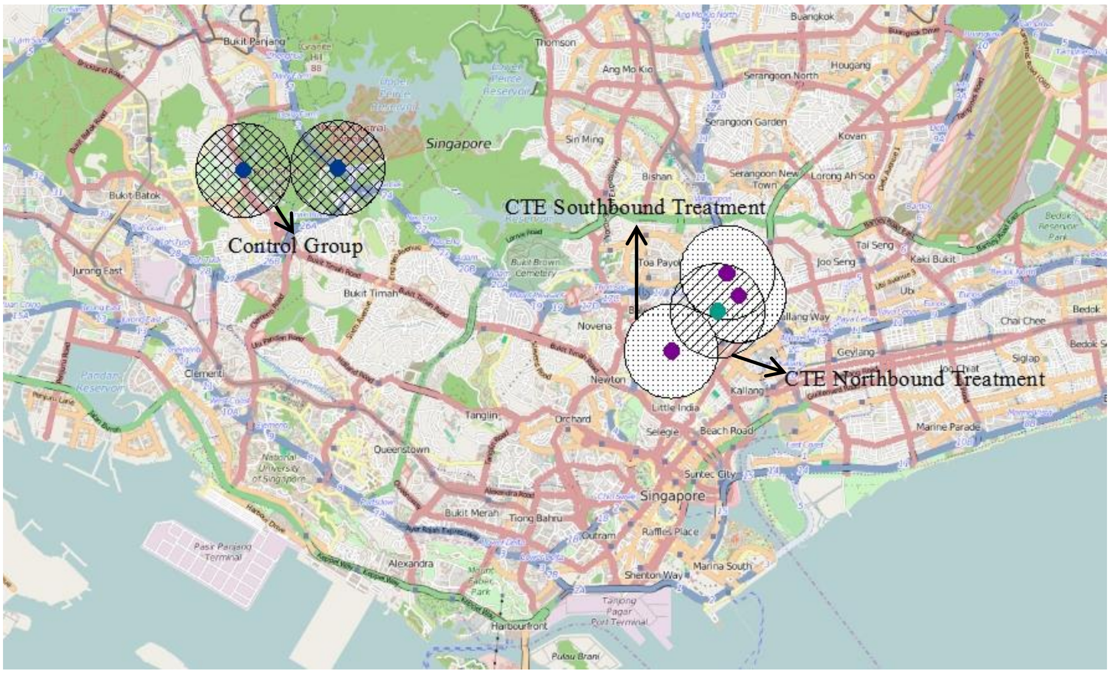
Table 9: Median Gross Monthly Income from Work of Full-Time Employed Residents

	2011	2012	2013	2014
LEVEL ($)	3,249	3,480	3,705	3,770
Real Change (%)*	2.9	2.5	4.0	0.7

*Deflated by Consumer Price Index for all items at 2009 prices (2009 = 100).

Source: Comprehensive Labor Force Survey, Ministry of Manpower

Figure 1: Boundary of the Test Areas: Treatment Group versus and Control Group



Note: The above figure shows the 1 kilometer boundary around the gantries that experienced toll increase in August 2013 (treatment group) and control group where there was no toll increase. CTE South Treatment experienced toll increase in the morning hours and CTE Northbound Treatment had toll increase in the evening hours. All the bus lines, excluding feeder bus lines and express bus lines, in the control and treatment area were selected as treatment group and control group respectively.

Appendix 1: Revised ERP rates with effect from 5 August 2013

Time Period	Current ERP Rates*	Change in Rates*	ERP Rates* w.e.f. 05-Aug-13
Southbound CTE after Braddell Road & PIE Slip Road into Southbound CTE – 4 gantries			
7:00 am – 7:30 am	$0.00	Increase by S$1.00	$1.00
7:30 am – 8:00 am	$4.00	Increase by S$1.00	$5.00
Northbound CTE Before PIE			
5:30 pm – 6:00 pm	$0.50	Increase by S$0.50	$1.00
6:00 pm – 6:30 pm	$1.00	Increase by S$1.00	$2.00
ECP (Fort Road) & KPE Slip Road onto ECP – 2 gantries			
8:30am – 9:00am	$5.00	Increase by S$1.00	$6.00

* ERP rate per Passenger Car Unit (PCU)

Source: http://www.lta.gov.sg/apps/news/page.aspx?c=2&id=58e453b0-88d3-464a-ae06-c2b90be7a10c

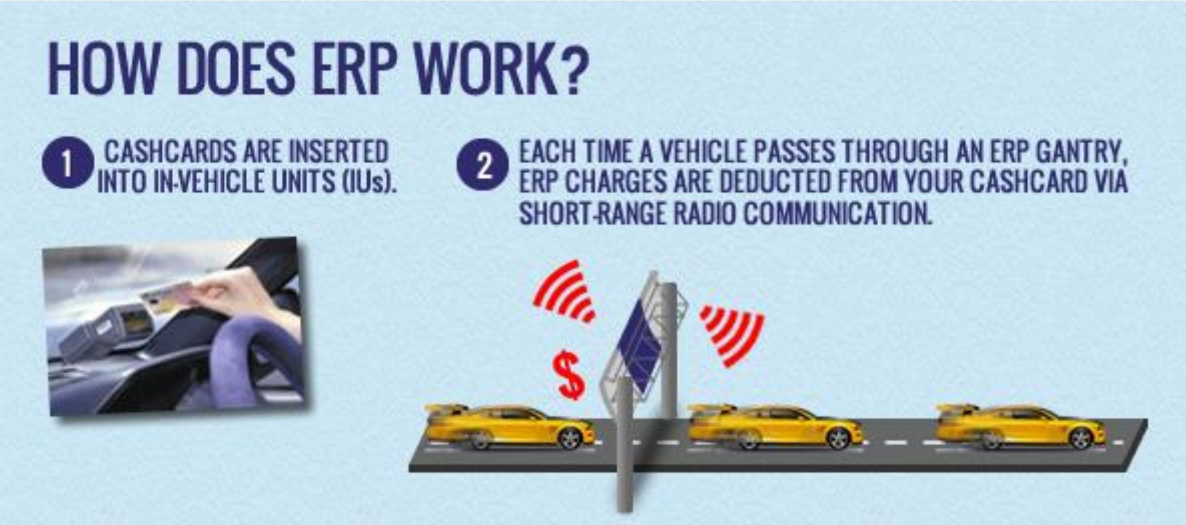
Note: The table show the revised rates for ERP tolls that came into effect from Monday, 5 August 2013. The rates for the other gantries would remain unchanged.

Appendix 2: Photo of ERP Gantry

Source: www.straitstimes.com

Note: The photo shows a ERP gantry in operation.

Appendix 3: Visual Description of ERP System



Note: The figure is obtained from www.lta.gov.sg. This illustration shows the appearance of In-vehicle Unit (IU) and the ERP charging process in Singapore.