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1 Can Hong Kong price-manage its public transportation's ridership?

2 Abstract

3 This paper is motivated by the usefulness of own- and cross-price elasticity
4 estimates in managing Hong Kong's demand for public transportation. It uses a 12-
5 year sample of monthly data from January 2006 to December 2017 to estimate a
6 Generalized Leontief system of six mode-specific passenger volume regressions. Its
7 key findings are: (1) the own-price elasticity estimates are -0.45 for taxi, -0.30 for
8 minibus, -0.24 for bus, -0.23 for ferry, -0.06 for tram, and -0.07 for train (i.e., Mass
9 Transit Railway); (2) the cross-price elasticity estimates are positive and smaller in
10 size than the own-price elasticity estimates; and (3) the aggregate own-price elasticity
11 estimate is -0.048 for the entire public transportation system. These findings of low
12 price responsiveness imply that reducing public transportation fares and raising
13 private transportation's average usage cost will likely have a minimal impact on Hong
14 Kong public transportation's ridership. Hence, mitigating Hong Kong's traffic
15 congestion and vehicular emissions may require such policy measures as restricting
16 private car ownership and improving Hong Kong public transportation's non-fare
17 attributes of accessibility and travel time performance.

18
19 **Keywords:** demand management, public transportation, passenger volume, price
20 elasticities, Hong Kong

1 **1. Introduction**

2 Hong Kong is a densely populated metropolis that houses 7.5 million residents
3 in a small geographic area of 1100 km² (Census and Statistics Department, 2019). Its
4 2017 per capita income of US\$46,000 rivals those of OECD countries (OECD, 2019).
5 According to Transport and Housing Bureau (2017), Hong Kong has a highly efficient
6 and affordable public transportation system,¹ comprising six modes of bus, minibus,
7 taxi, train (i.e., Mass Transit Railway (MTR)), tram, and ferry; see Fig. 1 and
8 Appendix 1.² When compared to Hong Kong’s population of 7.5 million, the
9 system’s total passenger volume is huge, approximately 12.6 million per day
10 (Transport Department, 2018).

11 As the Hong Kong Government sets the fares charged by public transportation
12 companies and affects private transportation’s usage cost through vehicular fuel taxes
13 and car registration fees, a substantive question thus arises: can Hong Kong price-
14 manage its public transportation’s ridership? This question’s policy relevance is
15 underscored by Hong Kong residents who daily see travel delays, like those living in
16 other large cities of the world (e.g., London, Paris, New York, Toronto, Singapore,
17 Tokyo, Beijing, and Shanghai).

¹ Hong Kong’s Census and Statistics Department reports that an average household’s spending on public transportation is less than 4% of the household’s total expenditure (Census and Statistics Department, 2019).

² The appendices are available from the corresponding author upon request.

1 Transport and Housing Bureau (2017) suggests that increasing public
2 transportation's utilization can ease Hong Kong's road congestion, thanks to the
3 relatively large passenger capacity of public transportation's non-taxi modes (e.g.,
4 bus, tram and train) when compared to that of private cars (e.g., sedan, sports utility
5 vehicle and van). It can also reduce Hong Kong's vehicular emissions because with
6 the exception of taxi, public transportation is more fuel-efficient than private
7 transportation on a per passenger basis. Thus, this paper is motivated by the
8 usefulness of price elasticity estimates in public transportation's demand management
9 and Hong Kong's lack of up to date own- and cross-price elasticity estimates.

10 Using a newly developed sample of monthly aggregate data for the 12-year
11 period of January 2006 to December 2017, it estimates a Generalized Leontief (GL)
12 system of six mode-specific passenger volume regressions to delineate the volume
13 effects of prices, income, weather, traffic congestion, road safety, mode-specific
14 capacities, MTR reliability, monthly public holidays, and monthly calendar days.
15 Presented below are the paper's key findings, which are, to the best of our knowledge,
16 new.

17 First, Panel A of Table 1 reports the own- and cross-price elasticity estimates
18 for Hong Kong's six public transportation modes.³ The own-price elasticity estimates

³ These estimates are near the low end of the ranges reported in literature surveys (e.g., Graham and Glaister, 2004; Balcombe et al., 2006; Litman, 2017) and meta analyses (e.g., Nijkamp and Pepping, 1998; Holmgren, 2007; Wardman, 2014; Fearnley et al., 2018).

1 are -0.45 for taxi, -0.30 for minibus, -0.24 for bus, -0.23 for ferry, -0.06 for tram, and -
2 0.07 for MTR⁴, suggesting that changing tram and MTR fares is unlikely to alter tram
3 and MTR passenger volumes. Thirty two of the 36 cross-price elasticity estimates are
4 below 0.1 and suggest limited inter-mode substitution. To be sure, larger substitution
5 effects do exist between two similar modes, as revealed by the 0.24 cross-price
6 elasticity estimate that measure taxi passenger volume's responsiveness to private car
7 use cost and the 0.17 estimate that measure minibus passenger volume's
8 responsiveness to bus fare.

9 Second, Hong Kong public transportation's total passenger volume is highly
10 price-inelastic. Its own-price elasticity estimate reported in Panel B of Table 1 is -
11 0.048, smaller in size than the range of -0.15 to -0.25 reported in Hau (1988), the only
12 econometric study of the demand for Hong Kong public transportation that we have
13 found via an extensive literature search.⁵

14 Third, the paper documents the expected percentage changes in Hong Kong
15 public transportation's total volume for three pricing proposals: (1) reduce the mode-
16 specific fares by 20%; (2) increase the private transportation usage cost by 10%; and

⁴ MTR's small own-price elasticity estimate corroborates the statistically insignificant estimate found by a recent study of 97 urbanized areas (Shyr et al., 2017).

⁵ The difference between our estimates and Hau's is attributable to the differences in passenger volume data, sample period, and estimation method. Specifically, our estimate comes from an estimation of a GL system, using the monthly passenger volumes of six public transportation modes for the 144-month sample period of January 2006 – December 2017. In contrast, Hau's estimates come from an estimation of linear and double-log regressions, using the annual aggregate volume data for the 22-year sample period of 1966-1987.

1 (3) combine (1) and (2). Mostly attributable to bus, minibus and taxi, the resulting
2 price-induced total volume changes are miniscule, only 1.33% even under Proposal 3.
3 As a result, implementing these proposals cannot materially increase Hong Kong
4 public transportation's ridership.

5 Fourth, Hong Kong public transportation's total passenger volume tends to be
6 lower in hot and wet than cool and dry weather, echoing the weather effects found by
7 Liu et al. (2015), Böcker et al. (2016), Zhou et al. (2017), and Tao et al. (2018).

8 Finally, MTR reliability does not have a statistically significant impact (p -
9 value > 0.2) on Hong Kong public transportation's total passenger volume. This
10 finding is at odds with the conclusion of Redman et al. (2013) that reliability
11 improvement can encourage public transportation ridership. A primary reason for this
12 finding is the lack of intra-year variations in the MTR reliability data, which hampers
13 a precise estimation of the volume effect of MTR's reliability performance.

14 This paper makes three contributions to the literature on the demand for public
15 transportation. First, it proposes a GL system to quantify the many price and non-price
16 effects on public transportation's mode-specific ridership, a research feat seldom seen
17 in extant studies. Second, it uses a recent sample of Hong Kong's monthly data to
18 demonstrate the GL system's real-world application, yielding a comprehensive set of
19 own- and cross-price elasticity estimates for all six public transportation modes.

1 Finally, it documents the limited effectiveness of three pricing proposals in managing
2 Hong Kong public transportation's ridership, suggesting that mitigating Hong Kong's
3 traffic congestion and vehicular emissions may entail restricting private car ownership
4 and improving public transportation's accessibility and travel time performance.

5 The rest of this paper proceeds as follows. Section 2 provides the paper's
6 background, presents the GL system, discusses our estimation strategy, proposes
7 testable hypotheses and elasticity calculations, and suggests pricing proposals for
8 demand management. Section 3 describes our monthly data sample. Section 4
9 discusses our empirical results. Section 5 concludes.

10 **2. Materials and methods**

11 2.1. Background

12 Price elasticity estimates play an important role in managing a city's
13 transportation demand (Balcombe et al., 2004). To see this point in Hong Kong's
14 context, let P_j denote the *average* passenger fare of public transportation mode j ($= 1$
15 for bus, ..., 6 for ferry),⁶ and P_7 the *average* cost of private car usage.⁷ Our use of
16 average price and cost data in the presence of nonlinear pricing triggers two important
17 econometric issues identified in the demand estimation literature (e.g., Hausman,

⁶ The average fare data are fare indices published by Hong Kong Transport Department, which are used in computing Hong Kong's consumer price index.

⁷ P_7 includes the costs for car purchase and O&M, motor fuel, and licenses and insurance. Its construction is based on the cost indices published by Hong Kong Transport Department.

1 1985; Berndt, 1991, Chapter 7; Reiss and White, 2005; Ito, 2014). For the sake of
2 readability, however, we decide to address these issues later in Section 4.

3 Based on Woo et al. (2018a), a price-induced percentage change in mode j 's
4 passenger volume is:

$$5 \quad d\ln X_j = \sum_k \varepsilon_{jk} d\ln P_k, \quad (1)$$

6 where $d\ln X_j = dX_j / X_j =$ percentage change in passenger volume X_j ; $\varepsilon_{jk} = \partial \ln X_j / \partial \ln P_k$
7 $= X_j$'s price elasticity with respect to P_k for $k = 1, \dots, 7$; and $d\ln P_k = dP_k / P_k =$
8 percentage change in P_k . Due to the unavailable data of passenger volume of private
9 car, our analysis is limited to a system of six mode-specific passenger volume and
10 seven prices.

11 In equation (1), ε_{jj} is mode j 's own-price elasticity and ε_{jk} cross-price elasticity
12 for $j \neq k$. While empirical studies of price elasticities abound, two general
13 observations can be made from literature surveys (e.g., Graham and Glaister, 2004;
14 Balcombe, et al., 2006; Litman, 2017) and meta analyses (e.g., Nijkamp and Pepping,
15 1998; Holmgren, 2007; Wardman, 2014; Fearnley et al., 2018). First, the main
16 research focus is own-price elasticity estimates, found to be diverse, negative and
17 relatively small in size (< 1.0). Second, cross-price elasticity estimates are small and
18 positive, reflecting modes like bus, train and tram having limited substitutability
19 because of their preset schedules, routes, and intra-route stops.

1 In this paper, we use Hong Kong’s aggregate data to estimate passenger
2 volume regressions. The popular specifications are the linear and double-log (Litman,
3 2017).⁸ Our literature search yields only one such study of Hong Kong public
4 transportation’s total passenger volume (Hau, 1988). Using annual data for the 22-
5 year period of 1966 – 1987, Hau (1988) estimates linear and double-log volume
6 regressions, finding own-price elasticity estimates of -0.15 to -0.25. While
7 informative, these estimates are based on a 20-year old sample that masks the
8 substitution possibilities among Hong Kong’s six public transportation modes, a
9 research challenge to be addressed in the sections below.

10 2.2. Model

11 2.2.1 Utility maximization

12 This section sketches the microeconomic foundation of our demand system for
13 analyzing Hong Kong public transportation’s mode-specific passenger volumes.
14 Intentionally brief for easy understanding by a general audience, it relies on the theory
15 of consumer demand (Deaton and Muellbauer, 1980) and household production
16 (Pollak and Wachter, 1975). In particular, it postulates a household’s utility
17 maximization as a two-stage optimization problem. In the first stage, the household
18 procures transportation services to meet its travel requirements triggered by such

⁸ Estimated in a single-equation setting, these two specifications’ popularity is due mainly to their implementation ease and consistency with the consumer theory of utility maximization (Hausman, 1981; Woo et al., 2012).

1 activities as going to work, shopping, social gathering, ..., etc. In the second stage, the
2 household chooses the optimal mix of activities and their associated travel
3 requirements to achieve its goal of utility maximization under budget and time
4 constraints.

5 An example of the two-stage optimization problem is the employment choice
6 made by a hypothetical college graduate majoring in computer science and living in a
7 suburban area far from Hong Kong's Central district where most financial companies
8 headquarter. Upon graduation, the graduate considers three job opportunities of
9 working as: (1) a self-employed programmer at home, (2) a junior engineer at a
10 nearby factory, and (3) a management trainee at a large bank in Central. The net
11 income from each job is the job-specific earning less work-related commuting costs.
12 The stage-1 solution is determined by each job's least-cost travel plan. While self-
13 employment does not require traveling, walking and public transportation are
14 preferred for the engineering job close to home and the trainee job in Central,
15 respectively. Under the admittedly simplifying assumption that all three jobs entail
16 similar effort and offer comparable career prospects, the stage-2 solution is the job
17 with the highest net income.

18 2.2.2 Aggregate travel cost

19 This section derives an aggregate travel cost formulation shaped by Hong

1 Kong's public data availability. It begins by considering an urban traveler going from
2 point A (e.g., home) to point B (e.g., a grocery store) who may walk, ride public
3 transportation, use private transportation, or employ a combination thereof. Each
4 least-cost trip is based on the stage-1 solution described in the last section.

5 The traveler chooses a daily plan for all of his/her $A \rightarrow B$ trips to minimize
6 his/her total travel cost, the sum of (a) the out-of-pocket cost at trip prices $\{P_j\}$; and
7 (b) the remaining cost that depends on commonly known non-price factors (e.g.,
8 travel comfort, travel time under uncongested road conditions, trip delays due to
9 traffic jams, service reliability, and road safety). Summing these daily plans over all
10 travelers and calendar days in a given month (e.g., January) yields Hong Kong's
11 monthly mode-specific passenger volumes $\{X_j\}$ for that month.

12 As the aggregate remaining cost R is unobservable, it is assumed to depend on
13 Z , a vector of M plausible non-price variables. These variables and their likely effect
14 on R are listed below:⁹

- 15 • Z_1 = monthly real GDP. An increase in Z_1 tends to increase R due to its effect on
16 Hong Kong's overall travel needs and private car usage. Specifically, rising
17 income tends to increase travel needs. However, it may also encourage private car

⁹ The variable listed below are arguably "too general" to capture time costs of travel. The more appropriate variables are average travel time per km, waiting time and accessibility to terminals for different modes. Unfortunately, the data for these more appropriate variables are unavailable. Whether this data limitation would invalidate our empirical findings is an issue best judged by our regression analysis' performance. Happily, Section 4 reports that our regression analysis and its findings are empirically reasonable.

1 usage that likely reduces the demand for public transportation. Hence, its net
2 effect on passenger volumes is an empirical issue to be settled by our regression
3 results described below.

- 4 • Z_2 = monthly number of vehicles per km of Hong Kong's road network. An
5 increase in Z_2 tends to increase R due to its impact on road congestion.
- 6 • Z_3 = MTR reliability measured by the monthly car-km per train failure causing
7 delays ≥ 5 minutes. An increase in Z_3 tends to increase R because reliability
8 deterioration disrupts travel plans and lengthens travel time.
- 9 • Z_4 = road safety measured by Hong Kong's monthly total number of traffic
10 accidents. An increase in Z_4 tends to increase R due to worsening road safety.
- 11 • Z_5 to Z_9 = mode-specific capacities measured by the monthly numbers of buses,
12 minibuses, taxis, MTR cars, and ferries.¹⁰ Rising capacities tend to reduce R .
- 13 • $Z_{10} - Z_{13}$ = monthly weather conditions measured by cooling degree month [=
14 $\max(\text{monthly average of daily maximum temperatures} - 18^\circ\text{C}, 0)$], heating degree
15 month [= $\max(18^\circ\text{C} - \text{monthly average of daily minimum temperatures}, 0)$],
16 monthly precipitation (mm), and monthly average humidity (%) (Woo et al.,
17 2018b). These variables are chosen to determine whether passenger volumes
18 depend on weather conditions. For example, bad weather is expected to increase

¹⁰ We exclude tram because its number hardly varies within the sample period.

1 the use of taxis because it discourages travelers from walking or waiting for buses.

2 It may also reduce the volumes for all modes because some travelers may choose

3 to abandon their planned trips. The net weather effects are therefore another issue

4 to be settled empirically via our regression analysis.

5 • Z_{14} = monthly number of public holidays whose increase reduces work-related

6 traveling but increases non-work-related trips. Its net effect is therefore *a priori*

7 unknown.

8 • Z_{15} = monthly number of calendar days because a longer month (e.g., January with

9 31 days) tends to have more monthly trips than a shorter month (e.g., February

10 with 28 days).

11 Finally, we use time trend t (= 1 for the first month and T for the last month in our

12 data sample) to capture the residual cost effects beyond those of \mathbf{Z} (e.g., expansion of

13 Hong Kong's infrastructure, passengers' changing tastes, ..., etc.).

14 Following Woo et al. (2015), we assume that the aggregate travel cost function

15 for a given month is:

16
$$C = G(\mathbf{P}, \mathbf{Z}, t) + R(\mathbf{Z}); \quad (2)$$

17 where $G = G(\mathbf{P}, \mathbf{Z}, t) = \sum_j P_j X_j^*$ = aggregate out-of-pocket cost at price vector \mathbf{P} ; and

18 $\{X_j^*\}$ = aggregate passenger volumes resulted from the cost minimization behavior of

19 urban travelers. In equation (2), $R(\mathbf{Z})$ is the arithmetic difference between $C > 0$ and

1 $G(\mathbf{P}, \mathbf{Z}, t) > 0$, measuring the unobservable aggregate remaining cost that has been
2 assumed not to depend on \mathbf{P} .

3 2.2.3 A GL system of passenger volume regressions

4 This section develops a GL system of passenger volume regressions by first
5 considering the various functional forms (e.g., GL, Translog, Minflex Laurent, Almost
6 Ideal Demand System (AIDS), and Flexible CES-GBC) described in Deaton and
7 Muellbauer (1980), Barnett et al. (1985), Pollak and Wales (1992), and Tishler and
8 Lipovetsky (1997). All these forms' estimation can use Hong Kong's publicly
9 available data, thus equally applicable to other cities with similar data availability.

10 We choose the GL specification (Diewert, 1971) for three reasons: suitability,
11 transparency and easy implementation. In terms of suitability, the GL specification
12 has global properties (Caves and Christensen, 1980; Barnett et al., 1985) well-suited
13 for quantifying the potentially low substitution among Hong Kong's public
14 transportation modes. In terms of transparency, it generates a system of linear
15 regressions that directly use passenger volumes as regressands, unlike other
16 specifications such as the Translog and AIDS that use cost shares. As a result, it is a
17 more transparent representation of how passenger volumes move with changes in their
18 price and non-price determinants. In terms of easy implementation, its linear structure
19 is relatively simple, yet capable of nesting all six public transportation modes in the

1 context of travel cost minimization explained in the preceding section.

2 Our GL parameterization of $G(\mathbf{P}, \mathbf{Z}, t)$ is:

3
$$G = \sum_j \sum_k \alpha_{jk} P_j^{1/2} P_k^{1/2} + \sum_j \sum_m \beta_{jm} P_j Z_m + \sum_j \tau_j P_j t. \quad (3)$$

4 Theoretical validity of $G(\mathbf{P}, \mathbf{Z}, t)$ necessitates the following restrictions: (1) symmetry:

5 $\alpha_{jk} = \alpha_{kj}$ for $j \neq k$; and (2) concavity in prices: $\alpha_{jk} \geq 0$ for $j \neq k$ (Diewert, 1971).

6 Invoking Shephard's Lemma (Varian, 1992), mode j 's passenger volume is:

7
$$X_j^* = \partial G / \partial P_j = \alpha_{jj} + \sum_{k \neq j} \alpha_{jk} (P_k / P_j)^{1/2} + \sum_m \beta_{jm} Z_m + \sum_j \tau_j t. \quad (4)$$

8 We verify that $\sum_j P_j X_j^* = G(\mathbf{P}, \mathbf{Z}, t)$ in equation (3). Further, C is homogeneous of

9 degree one in \mathbf{P} and R : $\lambda C = G(\lambda \mathbf{P}, \mathbf{Z}, t) + \lambda R(\mathbf{Z})$ for $\lambda > 0$, as required by a

10 theoretically valid cost function.

11 2.3. Estimation strategy

12 Data availability dictates our estimation strategy that comprises the following

13 elements. First, there are no data for private car passenger volume. Hence, we can

14 only estimate a GL system of six mode-specific passenger volume regressions for $j =$

15 1, ..., 6. Nevertheless, the resulting estimates for $(\alpha_{12}, \dots, \alpha_{67})$ suffice for our

16 calculation of own- and cross-price elasticities by mode, as demonstrated by equations

17 (7.a) and (7.b) below.¹¹

¹¹ Had private cars' passenger volume data been available, the GL system could have an additional equation. As the unbiased estimates for $(\alpha_{17}, \dots, \alpha_{67})$ can come from our estimation of the six-equation GL system, the main impact of the additional equation is a precision improvement that reduces the standard errors of these coefficients.

1 Second, the actual volume X_{jt} for observation t in our sample necessarily
2 differs from the postulated volume X_{jt}^* in equation (4). As a result, the right-hand-side
3 of mode j 's estimable equation contains an additive random error μ_{jt} with zero mean
4 and finite variance:

$$5 \quad X_{jt} = \alpha_{jj} + \sum_{k \neq j} \alpha_{jk} (P_{kt} / P_{jt})^{1/2} + \sum_m \beta_{jm} Z_{mt} + \tau_j t + \mu_{jt}. \quad (5)$$

6 Since $E(\mu_{jt}) = 0$, $E(X_{jt}) = E(X_{jt}^*)$. Further, modes j and k are substitutes when $\alpha_{jk} \neq 0$,
7 the basis for the testable hypotheses described below.

8 We use the iterated seemingly unrelated regression (ITSUR) technique in SAS
9 (2004) to estimate the GL system with cross-equation constraints of $\alpha_{jk} = \alpha_{kj}$ for $j \neq k$.
10 To ensure that the estimated $G(\mathbf{P}, \mathbf{Z}, t)$ is concave in prices, we impose the non-
11 negative constraints of $\alpha_{jk} \geq 0$ for $j \neq k$. If the binding constraints of $\alpha_{jk} = 0$ are
12 statistically insignificant at the 5% level, we infer that the estimated GL system is an
13 empirically plausible representation of the data generating process (DGP) underlying
14 our monthly passenger volume data.

15 Third, our monthly data can be non-stationary, casting doubt on our empirical
16 results' validity (Davidson and MacKinnon, 1993). Hence, we use the Phillips-Perron
17 (PP) test (Phillips and Perron, 1988) to determine each series' stationarity prior to our
18 ITSUR estimation. The PP test results help determine if the GL system should be
19 estimated using the level data as shown by equation (5) above, or the first-differenced

1 data as shown by equation (6) below:

$$2 \quad \Delta X_{jt} = \sum_{k \neq j} \alpha_{jk} \Delta(P_{kt} / P_{jt})^{1/2} + \sum_m \beta_{jm} \Delta Z_{mt} + \tau_j + \Delta \mu_{jt}, \quad (6)$$

3 where Δ = first difference operator (e.g., $\Delta X_{jt} = X_{jt} - X_{jt-1}$). Equation (6) highlights that

4 a public transportation mode's passenger volume change may occur due to (a)

5 changes in the price variables $\Delta(P_{kt} / P_{jt})^{1/2}$ or (b) variations in the non-price variables

6 ΔZ_{mt} (Stock and Watson, 2015, pp.427-430).¹²

7 2.4. Testable hypotheses and elasticity calculation

8 We use the Wald test to test the following null hypotheses of policy interests:

- 9 • **H1**: Passenger volumes are not price-sensitive, implying $\alpha_{jk} = 0$ for all $j \neq k$. If **H1**
10 is rejected, we infer that price-management of Hong Kong's public transportation
11 passenger volumes will have statistically significant effects.
- 12 • **H2**: Raising the private car usage cost does not move public transportation's
13 passenger volumes, implying $\alpha_{j7} = 0$ for all $j = 1, \dots, 6$. Rejecting **H2** implies that
14 raising P_7 will have a statistically significant impact on Hong Kong public
15 transportation's ridership.

16 To compute the price elasticities of public transportation, we use the formulae

17 in Woo et al. (2015). Based on equation (5), mode j 's monthly cross-price elasticity

¹² We assume μ_{jt} (or $\Delta \mu_{jt}$) follows an AR(n) process. We empirically select n based on the AR parameter estimates' statistical significance at the 5% level. Furthermore, we exclude non-price variables with highly insignificant estimates (p -value > 0.2) in **all** six passenger volume regressions.

1 formula for $j \neq k$ is:

$$2 \quad \varepsilon_{jkt} = \partial \ln X_{jt} / \partial \ln P_{kt} = 1/2 \alpha_{jk} (P_{kt} / P_{jt})^{1/2} / X_{jt}. \quad (7.a)$$

3 Mode j 's monthly own-price elasticity formula is:

$$4 \quad \varepsilon_{jtt} = \partial \ln X_{jt} / \partial \ln P_{jt} = -1/2 \sum_{k \neq j} \alpha_{jk} (P_{kt} / P_{jt})^{1/2} / X_{jt}. \quad (7.b)$$

5 As mode j 's passenger volume depends on the price ratios, its own- and cross-price
6 elasticities sum to zero (i.e., $\sum_k \varepsilon_{jkt} = 0$ for $k = 1, \dots, 7$).¹³ Thus, the mode-specific
7 elasticity estimates are the weighted average of the monthly estimates in our sample,
8 computed by equations (7.a) and (7.b).

9 To find Hong Kong public transportation system's aggregate own-price
10 elasticity, we first define the system's total volume: $X = X_1 + \dots + X_6$. We then find
11 $d \ln X = S_1 d \ln X_1 + \dots + S_6 d \ln X_6$, where $S_j = (X_j / X)$ and $d \ln X_j = \sum_k \varepsilon_{jk} d \ln P_k$ for $j =$
12 $1, \dots, 6$ and $k = 1, \dots, 7$. Because $\sum_k \varepsilon_{jk} = 0$, the aggregate own-price elasticity is

$$13 \quad d \ln X = -(S_1 \varepsilon_{17} + \dots + S_6 \varepsilon_{67}) \quad (8)$$

14 evaluated at $d \ln P_1 = \dots = d \ln P_6 = 1\%$ and $d \ln P_7 = 0$.

15 2.5. Price management of Hong Kong's public transportation demand

16 To inform Hong Kong's public debate on transportation, we consider three
17 pricing proposals to encourage the use of public transportation.¹⁴ We use equation (1)

¹³ We verify this point by recognizing that X_j for $j = 1, \dots, 6$ is homogeneous of degree zero in prices, implying $\sum_k P_k \partial X_j / \partial P_k = 0$ for $k = 1, \dots, 7$.

¹⁴ We do not consider whether each proposal is publicly acceptable to all stakeholders (e.g., the Hong Kong Government, public transportation users, public transportation providers, private car owners, and environment advocates), chiefly because such a consideration is well beyond the scope of this paper.

1 and the estimated price elasticities to compute the percentage changes in passenger
2 volumes caused by the implementation of each proposal, thus illustrating the elasticity
3 estimates' usefulness stated in Section 2.1. For empirical verification, we also use the
4 GL system's coefficients directly to repeat the impact calculation, as similarly done by
5 Woo et al. (2015). Section 4.3 below reports that the impact estimates thus obtained
6 closely match those based on the estimated elasticities.

7 The three pricing proposals are as follows:

- 8 • Proposal 1: Reduce all public transportation fares by 20%, possibly funded by the
9 Hong Kong Government's annual budget surplus, which is about HK\$138B
10 (US\$17.7B) in the 2017/18 fiscal year (Hong Kong Free Press, 2018).
- 11 • Proposal 2: Raise the private car price P_7 by 10%, which might come from fee
12 increases for car registration, tax increases for vehicular fuels, or both.
- 13 • Proposal 3: Combine the above proposals. This proposal imposes a less fiscal
14 burden on the Hong Kong Government than Proposal 1 when the fare reductions
15 are to be partially offset by the revenue generated under Proposal 2.

16 **3. Data description**

17 Our sample contains monthly data observed in the 12-year period of January
18 2006 to December 2017. Appendix 2 reports the monthly data's sources and
19 descriptive statistics. Figs. 2 and 3 graphically illustrate our monthly data. Fig. 2

1 shows that MTR and bus are the most popular modes. Thanks to the rail network's
2 expansion during the 12-year sample period, MTR's passenger volume rose gradually,
3 unlike the remaining modes' largely stable passenger volumes. The left-hand-side of
4 Fig. 3 shows the generally upward fare trends for bus, minibus, taxi and MTR, while
5 the right-hand-side portrays the rising ferry fare, the stepped tram fare, and the
6 fluctuating average cost of private car use.

7 **4. Results**

8 The PP test results reported in Appendix 2 show that, except for the price
9 series, all series are found to be stationary at the 5% level. All first-differenced series,
10 however, are found to be stationary. As a result, we decide to use the differenced data
11 to estimate equation (6).

12 4.1 ITSUR estimation

13 After determining that all regression residuals are stationary, we use Table 2 to
14 summarize our ITSUR regression results.¹⁵ The six regressions have a reasonable fit,
15 with adjusted R^2 values between 0.72 and 0.97. The regression residuals are found to
16 follow an $AR(n \leq 3)$ process because the fourth parameter estimates of an $AR(4)$
17 process turn out to be highly insignificant (p -value > 0.2).

18 We now turn our attention to the α_{jk} estimates for the square-rooted price

¹⁵ The SAS file, program, log and output listing are available from the corresponding author upon request.

1 ratios, which suggest that the estimated GL system is an empirically plausible DGP
2 for the differenced passenger volumes. While eight of the 21 estimates have been
3 restricted to zero, only one restriction ($\alpha_{45} = 0$) for the MTR and tram regressions is
4 statistically significant at the 5% level.¹⁶ The remaining 13 estimates are positive,
5 with the α_{12} estimate in the bus and minibus regressions being highly statistically
6 significant (p -value = 0.0014). There are two positive estimates that are significant at
7 the 10% level: (a) the α_{14} estimate (p -value = 0.0783) in the bus and MTR
8 regressions; and (b) the α_{23} estimate in the bus and minibus regressions (p -value =
9 0.0738). Taken together, the 21 α_{jk} estimates paint a picture of limited substitution
10 among the six public transportation modes and between public and private
11 transportation. This picture, however, does not mean that a price-management
12 proposal is completely ineffective because **H1** is decisively rejected by the highly
13 significant Wald statistic (p -value < 0.0001).

14 The Wald statistic for testing **H2** is insignificant (p -value = 0.3985), implying
15 that raising the average cost of private car use will not have a statistically significant
16 impact on Hong Kong public transportation's mode-specific passenger volumes,
17 echoing Hong Kong residents' car dependence documented by Cullinane and
18 Cullinane (2003).

¹⁶ This finding suggests that MTR and tram are compliments rather than substitutes. A plausible explanation is that some urban travelers (e.g., tourists) may use the tram service to reach their destination (e.g. the Victoria Peak) after leaving a MTR station (e.g. Central).

1 Looking at the β_{jm} estimates for the non-price variables with statistically
2 significant effects at the 5% level in at least one of the six regressions, we find that
3 GDP tends to increase passenger volumes, as does the number of total traffic
4 accidents. In contrast, hot and wet weather tends to reduce passenger volumes.
5 Further, a month with more public holidays tends to see a higher passenger volume
6 for ferry, not so for the remaining modes. This makes sense because Hong Kong
7 residents reduce their work-related travel on public holidays but increase their
8 holiday-related trips to the outlying islands. Finally, a longer month (e.g., January)
9 has, as expected, more passenger volume than a shorter one (e.g., February).

10 We end this section by discussing the non-price variables that have been
11 excluded from Table 2 due to their statistical insignificance. These variables are: (a)
12 the monthly number of vehicles per km of Hong Kong's road network; (b) MTR's
13 monthly car-km per train failure; (c) the monthly numbers of buses, minibuses, taxis,
14 MTR cars, trams, and ferries; and (d) the time trend. While (a) to (c) are expected to
15 matter, their minimal month-to-month variations prevent a precise detection of their
16 potentially significant volume effects. Finally, the estimates for the time trend
17 coefficients $\{\tau_j\}$ are statistically insignificant, reflecting the time trend's correlation
18 with the GDP and price series.

19 4.2 Final checks

1 We perform several final checks of our regression results reported in Section
2 4.1. First, we add the monthly unemployment rate and the time trend variable to the
3 estimation model. We find that the added variables are insignificant. We also replace
4 the total passenger volumes with per capita volumes and monthly GDP with per capita
5 GDP. The regression results thus obtained closely match those reported in Table 2.

6 Second, we use a double-log and a linear specification to estimate the six
7 passenger volume regressions. We find that some of the own-price estimated
8 coefficients are positive and significant (p -value < 0.05). These counter-intuitive
9 results cause us to abandon the double-log and the linear specification.

10 Finally, the price and cost series used in our GL estimation are based on
11 average fares and private car usage cost. Under nonlinear pricing, these average data
12 trigger two econometric issues. The first issue is whether consumers respond to
13 average or marginal prices. Recent evidence suggests that they respond to average
14 prices (Ito, 2014), lending support to our use of the average fare and cost data.

15 The second issue is the potential estimation bias caused by the average fares
16 and cost being volume-dependent and therefore endogenous (Hausman, 1985; Berndt,
17 1991, Chapter 7; Reiss and White, 2005).¹⁷ To assess the impact of this bias due to

¹⁷ Using electricity demand estimation as an example, a random shock (e.g., a summer heat wave) that increases electricity consumption also raises the average electricity price under an inclining block tariff. Thus, the electricity consumption and price data tend to be positively correlated, which in turn may shrink the presumably negative own-price elasticity estimate's size. Absent details of the fares' nonlinear structures, however, we cannot make a similar assessment on Hong Kong public transportation's mode-specific price elasticity estimates.

1 the price data's correlations with the GL system's random errors, we first consider the
2 following two-step procedure (Wooldridge, 2001, p.91):

- 3 • Step 1: Obtain the predicted values for P_{jt} based on the following regression: $P_{jt} =$
4 $Y_t \psi_j + \eta_{jt}$; where Y_t = vector of variables known to be uncorrelated with the GL
5 system's random errors; ψ_j = vector of coefficients; and η_{jt} = random error. The
6 variables included in Y_t are: (1) Hong Kong's monthly wage determined by Hong
7 Kong's aggregate labor market and import prices for gasoline and diesel set by the
8 world's fuel markets (Census and Statistics Department, 2019);¹⁸ and (2) binary
9 indicators for months of the year. Reflecting the supply side's cost reasons, our
10 choice of (1) is based on an OLS regression analysis that shows Hong Kong's
11 wage and fuel price variations cause transportation price variations. The same
12 OLS analysis supports our choice of (2) to account for residual cost variations not
13 captured by (1).
- 14 • Step 2: Repeat the ITSUR estimation after replacing P_{jt} 's actual values with
15 predicted values.

16 However, “[c]arrying out the two-step procedure explicitly makes one
17 susceptible to harmful mistakes” (Wooldridge, 2001, p.91) because the coefficients
18 from Step 2 can be inconsistent with incorrect standard errors. Hence, Our GL

¹⁸ Hong Kong's wage index is available at the quarterly level. The monthly wage index is found by linear interpolation.

1 system's coefficients are estimated by the iterated three-stage least squares (IT3SLS)
2 method (Wooldridge, 2001, pp.194-195). We find that using the IT3SLS technique
3 does not materially alter the empirics in Tables 1 and 2.¹⁹

4 4.3 Estimated percentage changes in passenger volumes

5 To demonstrate the usefulness of elasticity estimates in assessing a pricing
6 proposal's demand management effectiveness, we employ equation (1) and Table 1 to
7 estimate the percentage changes in Hong Kong's mode-specific passenger volumes.
8 Columns 2 to 7 of Table 3 show that the estimated changes under Proposal 1 are
9 small, ranging from 0.00% for MTR and tram to 4.97% for taxi. The changes under
10 Proposal 2 are smaller, with a range of 0.00% to 2.49%. Finally, Proposal 3 is
11 estimated to have mode-specific changes of 0.00% to 7.46%.

12 The last column of Table 3 reports the total percentage change estimates for
13 the entire system: 0.89% under Proposal 1, 0.44% under Proposal 2, and 1.33% under
14 Proposal 3. As all volume changes are found to be fairly small, price-managing Hong
15 Kong public transportation's ridership will only be minimally effective.²⁰

16 5. Conclusion

17 Using publicly available monthly data for the 12 year-period of 2006-2017, we

¹⁹ Appendix 3 reports the IT3SLS-based price elasticity estimates that are close to those in Table 1. Appendix 4 reports the IT3SLS regression results that resemble the ITSUR regression results in Table 2.

²⁰ For comparison, we use equation (11) in Woo et al. (2015, p.102) and the coefficients in Table 2 to estimate the percentage changes in passenger volumes. These alternatively developed estimates are close to those in Table 3.

1 estimate a GL system of six mode-specific volume regressions for Hong Kong's
2 public transportation system. Our main finding of low own- and cross-price elasticity
3 estimates has two policy implications. First, price-based demand management alone,
4 irrespective whether it is done via equiproportional or differential price changes, can
5 only have a minimal impact on Hong Kong public transportation's ridership. Second,
6 non-price-based measures such as capping the number of private cars and improving
7 the public transportation system's accessibility and travel time performance are likely
8 necessary to mitigate Hong Kong's road congestion and vehicular emissions.

9 We make the following closing remarks on how our results relate to previous
10 studies from Hong Kong and other parts of the world. First, our mode-specific own-
11 price elasticity estimates for taxi, bus, minibus and ferry are larger in size than the
12 elasticity estimates of -0.15 to -0.25 previously found by Hau (1988). However, the
13 same cannot be said for MTR and tram. Second, our aggregate price elasticity
14 estimate of -0.048 is smaller in size than those in Hau (1988). Finally, our price
15 elasticity estimates are also smaller in size than those reported for other parts of the
16 world in literature reviews (e.g., Graham and Glaister, 2004; Balcombe et al., 2006;
17 Litman, 2017) and meta analyses (e.g., Nijkamp and Pepping, 1998; Holmgren, 2007;
18 Wardman, 2014; Fearnley et al., 2018). These remarks imply that a city should,
19 whenever possible, develop its own set of updated price elasticity estimates with

1 sufficient details for assessing the effectiveness of price-managing its public
2 transportation system. This is because overstating the effectiveness of a fare decrease
3 proposal may cause the city to overlook non-fare-based proposals that can better
4 promote the city's public transportation ridership.

5 To conclude, our demand system estimation is useful for determining whether
6 price-management is effective in promoting public transportation ridership.

7 Unfortunately, it cannot determine the effectiveness of non-fare-based proposals yet to
8 be implemented, chiefly because it uses aggregate data that are necessarily *ex post*. A
9 more suitable approach is discrete choice modeling of survey data collected from a
10 large sample of urban travelers (Train, 1986, 2003; Hensher et al., 2005), a research
11 endeavor that is well beyond the intent and scope of our paper.

12 **Acknowledgement**

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- 3

4 Table 1. Hong Kong's own- and cross-price elasticity estimates based on the regression results in Table 2; sample period: January 2006 - December 2017

5

6 Panel A: Disaggregate elasticities (ε_{jk} for $j = 1, \dots, 6$ and $k = 1, \dots, 7$) by public transportation mode

X_j : Passenger volume of mode j	P_1 : Bus fare	P_2 : Minibus fare	P_3 : Taxi fare	P_4 : MTR fare	P_5 : Tram fare	P_6 : Ferry fare	P_7 : Average cost of private car use
X_1 : Bus	-0.2350	0.0807	0.0224	0.0735	0.0019	0.0000	0.0565
X_2 : Minibus	0.1725	-0.3003	0.0618	0.0000	0.0001	0.0104	0.0556
X_3 : Taxi	0.0916	0.1184	-0.4470	0.0000	0.0000	0.0000	0.2371
X_4 : MTR	0.0648	0.0000	0.0000	-0.0662	0.0000	0.0014	0.0000
X_5 : Tram	0.0374	0.0007	0.0000	0.0000	-0.0629	0.0248	0.0000
X_6 : Ferry	0.0000	0.1446	0.0000	0.0483	0.0376	-0.2348	0.0043

7

8 Panel B: Aggregate own- and cross-price elasticity estimates of the Hong Kong public transportation's total passenger volume

Own-price elasticity with respect to public transportation's passenger fares	Cross-price elasticity with respect to the average cost of private car usage
-0.0480	0.0480

9

10 Notes: (1) Panel A shows that taxi has the most price-responsive volume, followed by minibus, bus, ferry, MTR and tram. However, all modes have price-inelastic volumes.

11 (2) Section 2 shows that mode-specific passenger volume X_j depends on the price ratios, implying that its own- and cross-price elasticities sum to zero (i.e., $\sum_k \varepsilon_{jk} = 0$
 12 for $k = 1, \dots, 7$).

13 (3) The aggregate own-price elasticity estimate in Panel B is based on equation (8) in the main text. Because $\sum_k \varepsilon_{jk} = 0$, the aggregate own- and cross-price elasticity
 14 estimates have the same size.

15

16 Table 2. Summary of ITSUR results for the GL system of mode-specific passenger volume regressions based on equation (6) and monthly first-differenced data for the 12-
 17 year period of January 2006 - December 2017; standard errors in (); coefficients significant at the 5% level in **bold**

Coefficient: variable	Passenger volume regression j for $j = 1, \dots, 6$											
	1: Bus		2: Minibus		3: Taxi		4: MTR		5: Tram		6: Ferry	
Adjusted R^2	0.899		0.9662		0.7736		0.9065		0.7176		0.7923	
Number of significant AR parameter estimates	3		3		1		2		3		3	
$\alpha_{jk}: \Delta(P_k / P_j)^{1/2}$ for $j \neq k$, where P_1 = average bus fare, ..., P_7 = average usage cost of private cars	α_{12}	19222.95 (5896.90)	α_{12}	19222.95 (5896.90)	α_{13}	5400.06 (7541.30)	α_{14}	17577.33 (9903.80)	α_{15}	456.54 (2242.20)	α_{16}	0.00 (0.00)
	α_{13}	5400.06 (7541.30)	α_{23}	7039.56 (3904.80)	α_{23}	7039.56 (3904.80)	α_{24}	0.00 (0.00)	α_{25}	9.11 (2459.30)	α_{26}	1189.18 (2877.10)
	α_{14}	17577.33 (9903.80)	α_{24}	0.00 (0.00)	α_{34}	0.00 (0.00)	α_{34}	0.00 (0.00)	α_{35}	0.00 (0.00)	α_{36}	0.00 (0.00)
	α_{15}	456.54 (2242.20)	α_{25}	9.11 (2459.30)	α_{35}	0.00 (0.00)	α_{45}	0.00 (0.00)	α_{45}	0.00 (0.00)	α_{46}	398.91 (1706.70)
	α_{16}	0.00 (0.00)	α_{26}	1189.18 (2877.10)	α_{36}	0.00 (0.00)	α_{46}	398.91 (1706.70)	α_{56}	309.79 (1350.30)	α_{56}	309.79 (1350.30)
	α_{17}	13346.31 (14507.00)	α_{27}	6188.26 (5092.80)	α_{37}	13967.18 (9473.30)	α_{47}	0.00 (0.00)	α_{57}	0.00 (0.00)	α_{67}	34.84 (1875.50)
$\beta_{j1}: \Delta(\text{monthly real GDP})$	0.03 (0.03)		0.01 (0.01)		0.02 (0.01)		0.27 (0.03)		0.00 (0.00)		0.01 (0.00)	
$\beta_{j4}: \Delta(\text{monthly total number of traffic accidents})$	3.33 (1.62)		1.68 (0.43)		0.65 (0.58)		7.33 (1.98)		0.18 (0.19)		-0.54 (0.16)	

β_{j10} : Δ (monthly cooling degree month)	-54.44 (58.21)	-4.15 (15.52)	81.83 (24.43)	-224.29 (73.83)	-36.67 (7.33)	-13.06 (5.32)
β_{j11} : Δ (monthly heating degree month)	-567.11 (160.90)	-184.57 (43.72)	102.20 (59.75)	-289.85 (200.90)	-81.70 (19.24)	-69.76 (14.93)
β_{j12} : Δ (monthly precipitation)	-5.16 (1.01)	-1.02 (0.27)	-0.48 (0.37)	-2.64 (1.25)	-0.36 (0.12)	-0.12 (0.09)
β_{j13} : Δ (monthly average humidity)	-101.17 (39.67)	-41.56 (10.55)	-13.83 (14.43)	-103.62 (48.94)	-13.86 (4.62)	-11.66 (3.61)
β_{j14} : Δ (number of public holidays)	-604.31 (105.80)	-363.33 (30.40)	-152.22 (37.68)	-936.03 (131.00)	-16.36 (11.60)	39.78 (11.45)
β_{j15} : Δ (number of calendar days)	3333.78 (258.70)	1629.56 (65.79)	724.12 (102.40)	2515.76 (318.70)	237.82 (30.70)	166.70 (23.79)

- 18 Notes: (1) Eight of the 21 $\alpha_{j \neq k}$ estimates have been constrained to zero, implying that their standard errors are also equal to zero. Only the α_{45} coefficient estimate in *italic* is
19 negative and significant at the 5% level but has been constrained to zero. We therefore infer that the estimated GL system with non-negative constraints on
20 coefficients $\{\alpha_{j \neq k}\}$ is an empirically plausible representation of the data generating process for Hong Kong public transportation's passenger volume data.
21 (2) The p -values of the Wald statistic are: (a) < 0.01 for testing **H1**: $\alpha_{jk} = 0$ for all $j \neq k$; and (b) 0.39 for testing **H2**: $\alpha_{j7} = 0$ for all j .

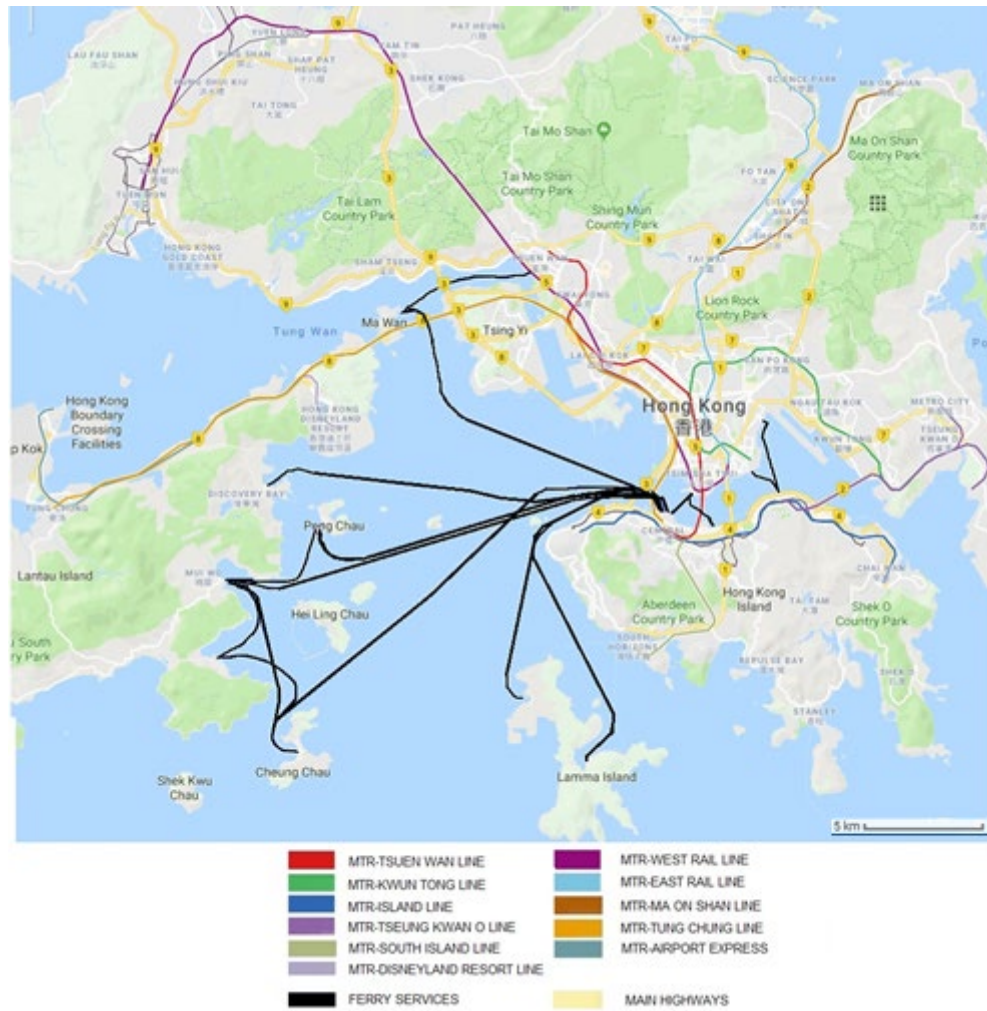
22 Table 3. Percentage change in the Hong Kong public transportation mode-specific passenger volumes based on equation (1) in the main text

Proposal description	Bus	Minibus	Taxi	MTR	Tram	Ferry	Total
(1) Reduce all public transportation fares P_1 to P_6 by 20%,	1.12%	1.12%	4.97%	0.00%	0.00%	0.09%	0.89%
(2) Raise the average cost of private car use P_7 by 10%	0.56%	0.56%	2.49%	0.00%	0.00%	0.05%	0.44%
(3) Combine (1) and (2)	1.68%	1.68%	7.46%	0.00%	0.00%	0.14%	1.33%

23 Notes: (1) Taxi has the largest estimated changes, followed by bus and minibus. The remaining modes of MTR, tram and ferry are unaffected by the proposals’
 24 implementation.

25 (2) The total percentage change is a weighted average of the mode-specific percentage changes, with weights equal to the mode-specific volumes in 2017.

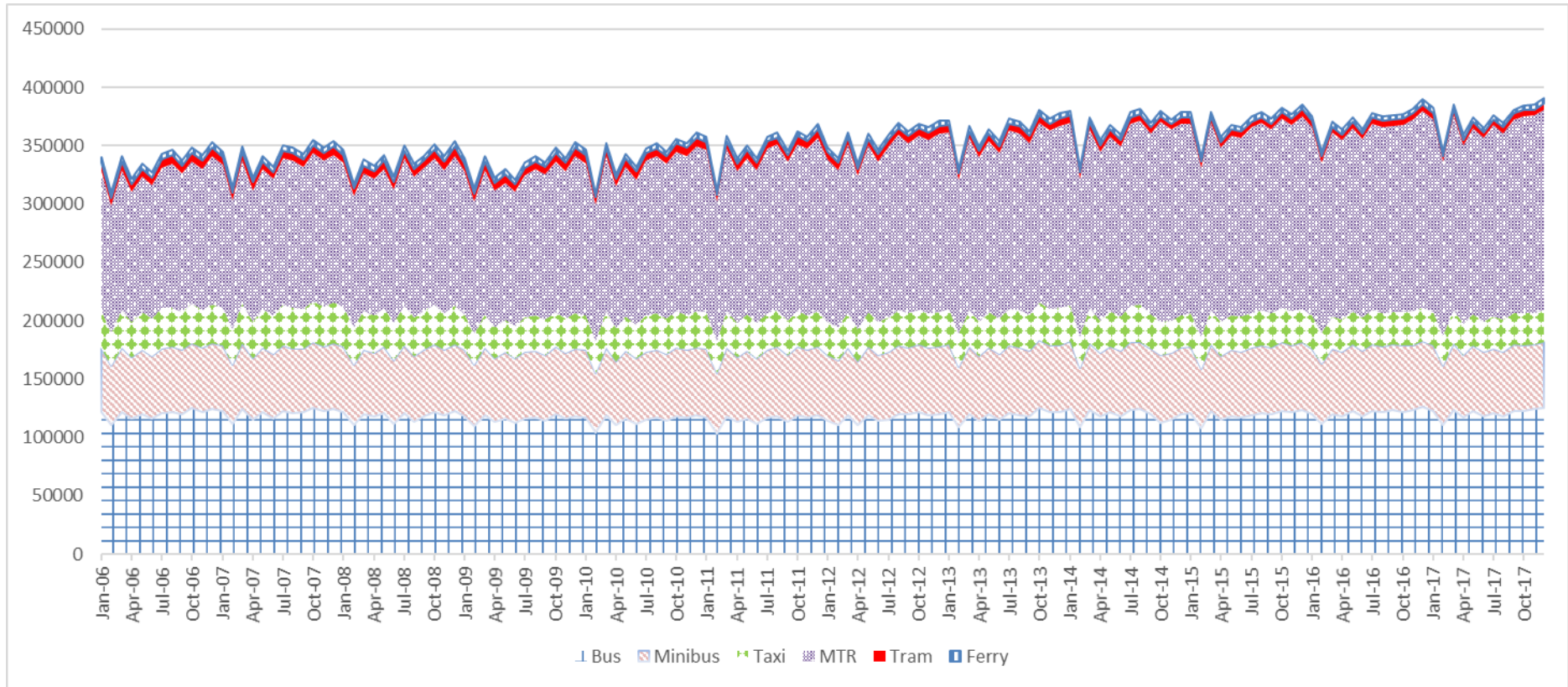
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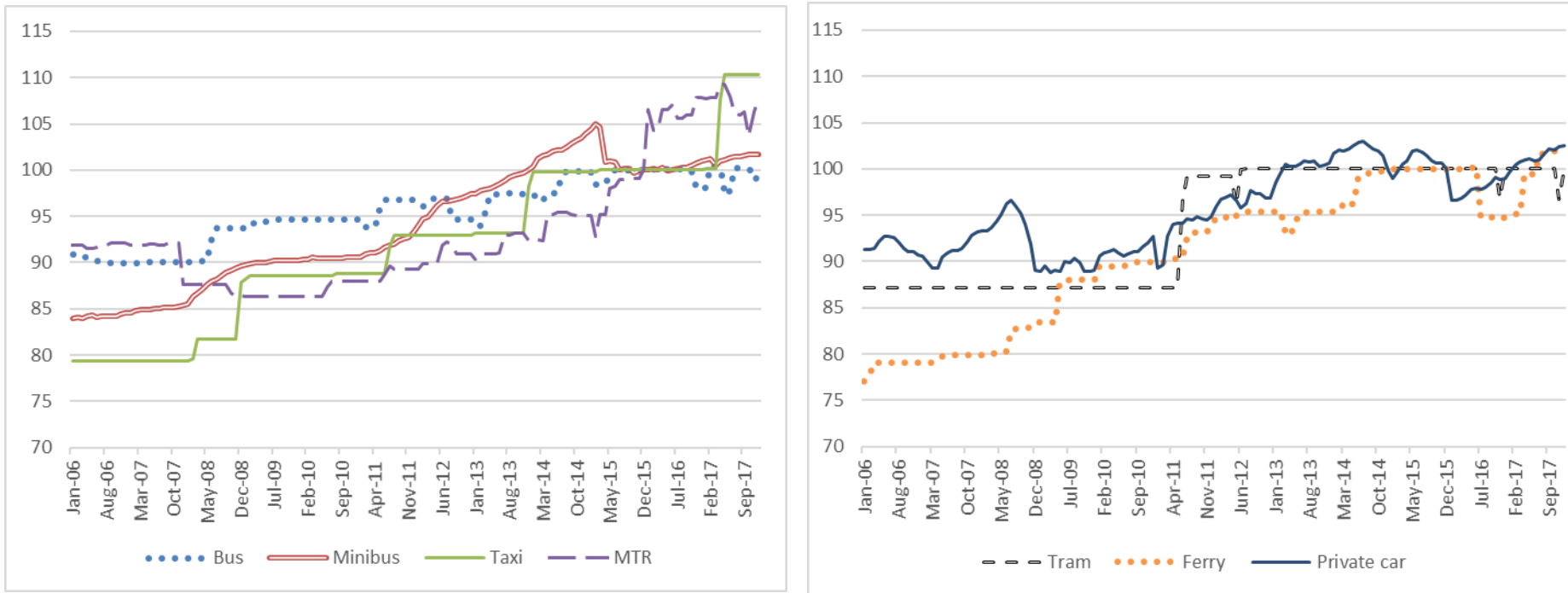
Fig.1. Hong Kong's MTR network, ferry routes and main highways



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31 Fig. 2. Monthly passenger volumes (000) of Hong Kong's public transportation system for the 12-year period of January 2006 - December 2017

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33 Fig. 3. Hong Kong's monthly transportation price indices for the 12-year period of January 2006 - December 2017

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