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

Woo, Chi Keung; Liu, Y.; Cao, Kang Hua; Zarnikau, J.

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Abstract

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

Keywords: demand management, public transportation, passenger volume, price elasticities, Hong Kong

1. Introduction

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

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

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

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

First, Panel A of Table 1 reports the own- and cross-price elasticity estimates 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).

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

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

Third, the paper documents the expected percentage changes in Hong Kong public transportation's total volume for three pricing proposals: (1) reduce the mode-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.

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

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

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

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

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

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

2. Materials and methods

2.1. Background

Price elasticity estimates play an important role in managing a city's transportation demand (Balcombe et al., 2004). To see this point in Hong Kong's context, let P_j denote the ***average*** passenger fare of public transportation mode j (= 1 for bus, …, 6 for ferry),[6] and P_7 the ***average*** cost of private car usage.[7] Our use of average price and cost data in the presence of nonlinear pricing triggers two important 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.

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

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

$$\mathrm{d}lnX_j \quad = \quad \Sigma_k \, \varepsilon_{jk} \, \mathrm{d}lnP_k, \qquad (1)$$

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

In equation (1), ε_{jj} is mode j's own-price elasticity and ε_{jk} cross-price elasticity for $j \neq k$. While empirical studies of price elasticities abound, two general observations can be made from 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). First, the main research focus is own-price elasticity estimates, found to be diverse, negative and relatively small in size (< 1.0). Second, cross-price elasticity estimates are small and positive, reflecting modes like bus, train and tram having limited substitutability because of their preset schedules, routes, and intra-route stops.

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

2.2. Model

2.2.1 Utility maximization

This section sketches the microeconomic foundation of our demand system for analyzing Hong Kong public transportation's mode-specific passenger volumes. Intentionally brief for easy understanding by a general audience, it relies on the theory of consumer demand (Deaton and Muellbauer, 1980) and household production (Pollak and Wachter, 1975). In particular, it postulates a household's utility maximization as a two-stage optimization problem. In the first stage, the household 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).

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

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

2.2.2 Aggregate travel cost

This section derives an aggregate travel cost formulation shaped by Hong

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

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

As the aggregate remaining cost R is unobservable, it is assumed to depend on $\boldsymbol{Z}$, a vector of M plausible non-price variables. These variables and their likely effect on R are listed below:[9]

- Z_1 = monthly real GDP. An increase in Z_1 tends to increase R due to its effect on Hong Kong's overall travel needs and private car usage. Specifically, rising 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.

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

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

the use of taxis because it discourages travelers from walking or waiting for buses. It may also reduce the volumes for all modes because some travelers may choose to abandon their planned trips. The net weather effects are therefore another issue to be settled empirically via our regression analysis.

- Z_{14} = monthly number of public holidays whose increase reduces work-related traveling but increases non-work-related trips. Its net effect is therefore *a priori* unknown.
- Z_{15} = monthly number of calendar days because a longer month (e.g., January with 31 days) tends to have more monthly trips than a shorter month (e.g., February with 28 days).

Finally, we use time trend t (= 1 for the first month and T for the last month in our data sample) to capture the residual cost effects beyond those of $\boldsymbol{Z}$ (e.g., expansion of Hong Kong's infrastructure, passengers' changing tastes, …, etc.).

Following Woo et al. (2015), we assume that the aggregate travel cost function for a given month is:

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

where $G = G(\boldsymbol{P}, \boldsymbol{Z}, t) = \Sigma_j P_j X_j^*$ = aggregate out-of-pocket cost at price vector $\boldsymbol{P}$; and $\{X_j^*\}$ = aggregate passenger volumes resulted from the cost minimization behavior of urban travelers. In equation (2), $R(\boldsymbol{Z})$ is the arithmetic difference between $C > 0$ and

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

2.2.3 A GL system of passenger volume regressions

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

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

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

$$G \quad = \quad \Sigma_j \, \Sigma_k \, \alpha_{jk} \, P_j^{1/2} \, P_k^{1/2} + \Sigma_j \, \Sigma_m \, \beta_{jm} \, P_j \, Z_m + \Sigma_j \, \tau_j \, P_j \, t. \tag{3}$$

Theoretical validity of $G(\boldsymbol{P}, \boldsymbol{Z}, t)$ necessitates the following restrictions: (1) symmetry: $\alpha_{jk} = \alpha_{kj}$ for $j \neq k$; and (2) concavity in prices: $\alpha_{jk} \geq 0$ for $j \neq k$ (Diewert, 1971). Invoking Shephard's Lemma (Varian, 1992), mode j's passenger volume is:

$$X_j^* = \partial G / \partial P_j = \alpha_{jj} + \Sigma_{k \neq j} \, \alpha_{jk} \, (P_k / P_j)^{1/2} + \Sigma_m \, \beta_{jm} \, Z_m + \Sigma_j \, \tau_j \, t. \tag{4}$$

We verify that $\Sigma_j \, P_j \, X_j^* = G(\boldsymbol{P}, \boldsymbol{Z}, t)$ in equation (3). Further, C is homogeneous of degree one in $\boldsymbol{P}$ and R: $\lambda C = G(\lambda \boldsymbol{P}, \boldsymbol{Z}, t) + \lambda \, R(\boldsymbol{Z})$ for $\lambda > 0$, as required by a theoretically valid cost function.

2.3. Estimation strategy

Data availability dictates our estimation strategy that comprises the following elements. First, there are no data for private car passenger volume. Hence, we can only estimate a GL system of six mode-specific passenger volume regressions for j = 1, …, 6. Nevertheless, the resulting estimates for (α_{12}, …, α_{67}) suffice for our calculation of own- and cross-price elasticities by mode, as demonstrated by equations (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 (α_{17}, …, α_{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.

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

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

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

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

Third, our monthly data can be non-stationary, casting doubt on our empirical results' validity (Davidson and MacKinnon, 1993). Hence, we use the Phillips-Perron (PP) test (Phillips and Perron, 1988) to determine each series' stationarity prior to our ITSUR estimation. The PP test results help determine if the GL system should be estimated using the level data as shown by equation (5) above, or the first-differenced data as shown by equation (6) below:

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

where Δ = first difference operator (e.g., $\Delta X_{jt} = X_{jt} - X_{jt-1}$). Equation (6) highlights that a public transportation mode's passenger volume change may occur due to (a) changes in the price variables $\Delta(P_{kt} / P_{jt})^{1/2}$ or (b) variations in the non-price variables ΔZ_{mt} (Stock and Watson, 2015, pp.427-430).[12]

2.4. Testable hypotheses and elasticity calculation

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

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

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

formula for $j \neq k$ is:

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

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

$$\varepsilon_{jjt} = \partial \ln X_{jt} / \partial \ln P_{jt} = -\ 1/2\ \Sigma_{k \neq j}\ \alpha_{jk} (P_{kt} / P_{jt})^{1/2} / X_{jt}. \qquad (7.b)$$

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

To find Hong Kong public transportation system's aggregate own-price elasticity, we first define the system's total volume: $X = X_1 + \ldots + X_6$. We then find $dlnX = S_1\ dlnX_1 + \ldots + S_6\ dlnX_6$, where $S_j = (X_j / X)$ and $dlnX_j = \Sigma_k\ \varepsilon_{jk}\ dlnP_k$ for $j = 1, \ldots, 6$ and $k = 1, \ldots, 7$. Because $\Sigma_k\ \varepsilon_{jk} = 0$, the aggregate own-price elasticity is

$$dlnX = -\ (S_1 \varepsilon_{17} + \ldots + S_6\ \varepsilon_{67}) \qquad (8)$$

evaluated at $dlnP_1 = \ldots = dlnP_6 = 1\%$ and $dlnP_7 = 0$.

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

To inform Hong Kong's public debate on transportation, we consider three 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 $j = 1, \ldots, 6$ is homogeneous of degree zero in prices, implying $\Sigma_k\ P_k\ \partial X_j / \partial P_k = 0$ for $k = 1, \ldots, 7$.

[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.

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

The three pricing proposals are as follows:

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

3. Data description

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

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

4. Results

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

4.1 ITSUR estimation

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

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.

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

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

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

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

4.2 Final checks

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

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

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

The second issue is the potential estimation bias caused by the average fares and cost being volume-dependent and therefore endogenous (Hausman, 1985; Berndt, 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.

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

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

However, "[c]arrying out the two-step procedure explicitly makes one susceptible to harmful mistakes" (Wooldridge, 2001, p.91) because the coefficients 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.

system's coefficients are estimated by the iterated three-stage least squares (IT3SLS) method (Wooldridge, 2001, pp.194-195). We find that using the IT3SLS technique does not materially alter the empirics in Tables 1 and 2.[19]

4.3 Estimated percentage changes in passenger volumes

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

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

5. Conclusion

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.

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

We make the following closing remarks on how our results relate to previous studies from Hong Kong and other parts of the world. First, our mode-specific own-price elasticity estimates for taxi, bus, minibus and ferry are larger in size than the elasticity estimates of -0.15 to -0.25 previously found by Hau (1988). However, the same cannot be said for MTR and tram. Second, our aggregate price elasticity estimate of -0.048 is smaller in size than those in Hau (1988). Finally, our price elasticity estimates are also smaller in size than those reported for other parts of the world in literature reviews (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). These remarks imply that a city should, whenever possible, develop its own set of updated price elasticity estimates with sufficient details for assessing the effectiveness of price-managing its public transportation system. This is because overstating the effectiveness of a fare decrease proposal may cause the city to overlook non-fare-based proposals that can better promote the city's public transportation ridership.

To conclude, our demand system estimation is useful for determining whether price-management is effective in promoting public transportation ridership. Unfortunately, it cannot determine the effectiveness of non-fare-based proposals yet to be implemented, chiefly because it uses aggregate data that are necessarily *ex post*. A more suitable approach is discrete choice modeling of survey data collected from a large sample of urban travelers (Train, 1986, 2003; Hensher et al., 2005), a research endeavor that is well beyond the intent and scope of our paper.

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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

Panel A: Disaggregate elasticities (ε_{jk} for j = 1, …, 6 and k = 1, …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

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

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.

(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., $\Sigma_k\ \varepsilon_{jk} = 0$ for k = 1, …, 7).

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

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-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, …, 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
α_{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)
β_{j1}: Δ(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)
β_{j4}: Δ(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	-4.15	**81.83**	**-224.29**	**-36.67**	**-13.06**
	(58.21)	(15.52)	(24.43)	(73.83)	(7.33)	(5.32)
β_{j11}: Δ(monthly heating degree month)	**-567.11**	**-184.57**	102.20	-289.85	**-81.70**	**-69.76**
	(160.90)	(43.72)	(59.75)	(200.90)	(19.24)	(14.93)
β_{j12}: Δ(monthly precipitation)	**-5.16**	**-1.02**	-0.48	**-2.64**	**-0.36**	-0.12
	(1.01)	(0.27)	(0.37)	(1.25)	(0.12)	(0.09)
β_{j13}: Δ(monthly average humidity)	**-101.17**	**-41.56**	-13.83	**-103.62**	**-13.86**	**-11.66**
	(39.67)	(10.55)	(14.43)	(48.94)	(4.62)	(3.61)
β_{j14}: Δ(number of public holidays)	**-604.31**	**-363.33**	**-152.22**	**-936.03**	-16.36	**39.78**
	(105.80)	(30.40)	(37.68)	(131.00)	(11.60)	(11.45)
β_{j15}: Δ(number of calendar days)	**3333.78**	**1629.56**	**724.12**	**2515.76**	**237.82**	**166.70**
	(258.70)	(65.79)	(102.40)	(318.70)	(30.70)	(23.79)

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 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 coefficients $\{\alpha_{j\neq k}\}$ is an empirically plausible representation of the data generating process for Hong Kong public transportation's passenger volume data.

(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.

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%

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' implementation.

(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.

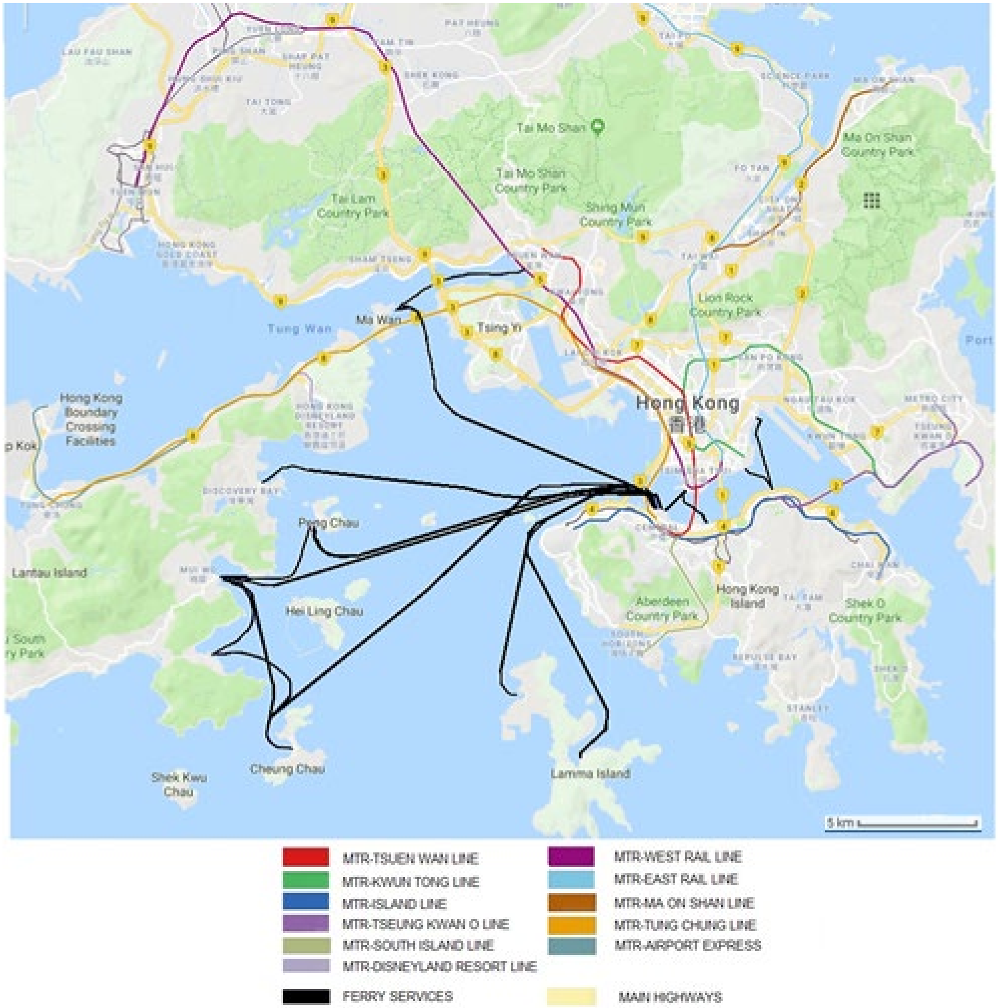

Fig.1. Hong Kong's MTR network, ferry routes and main highways

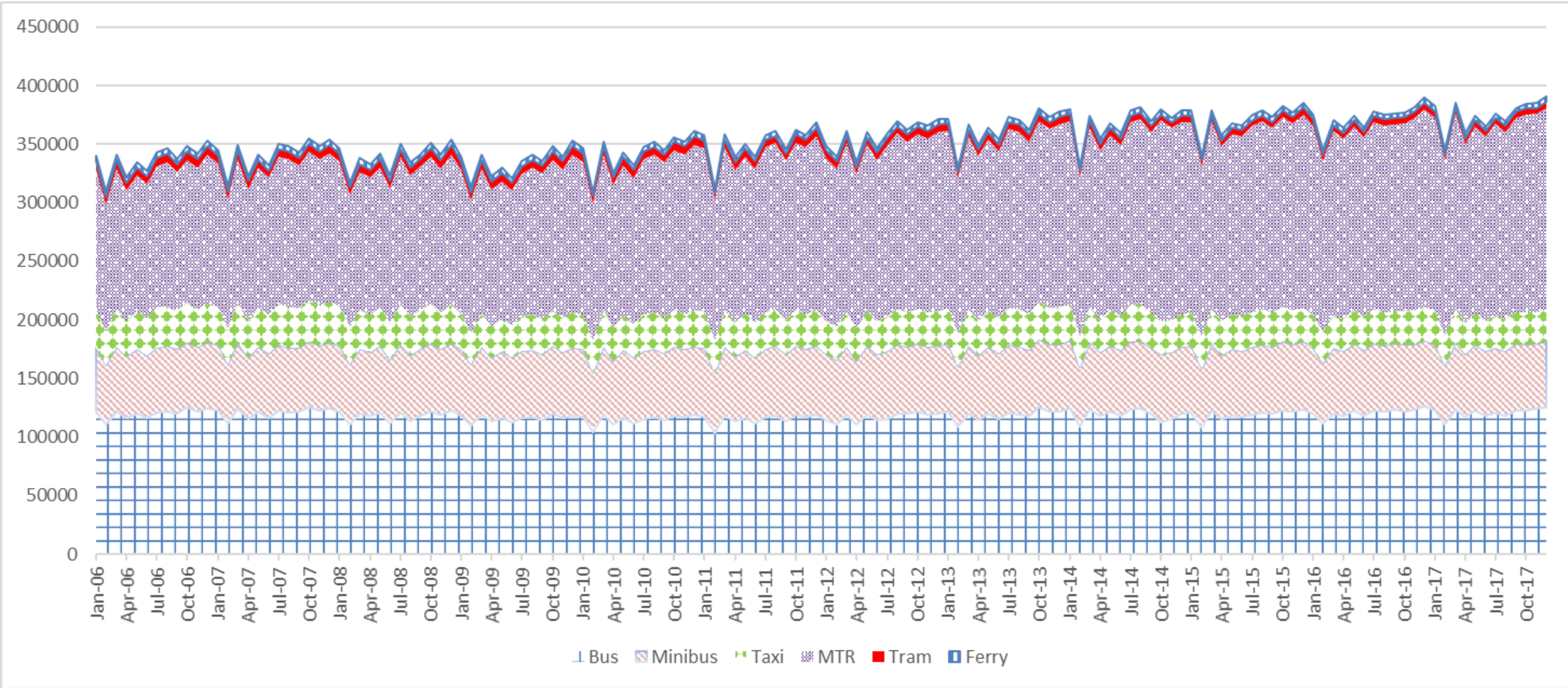

Fig. 2. Monthly passenger volumes (000) of Hong Kong's public transportation system for the 12-year period of January 2006 - December 2017

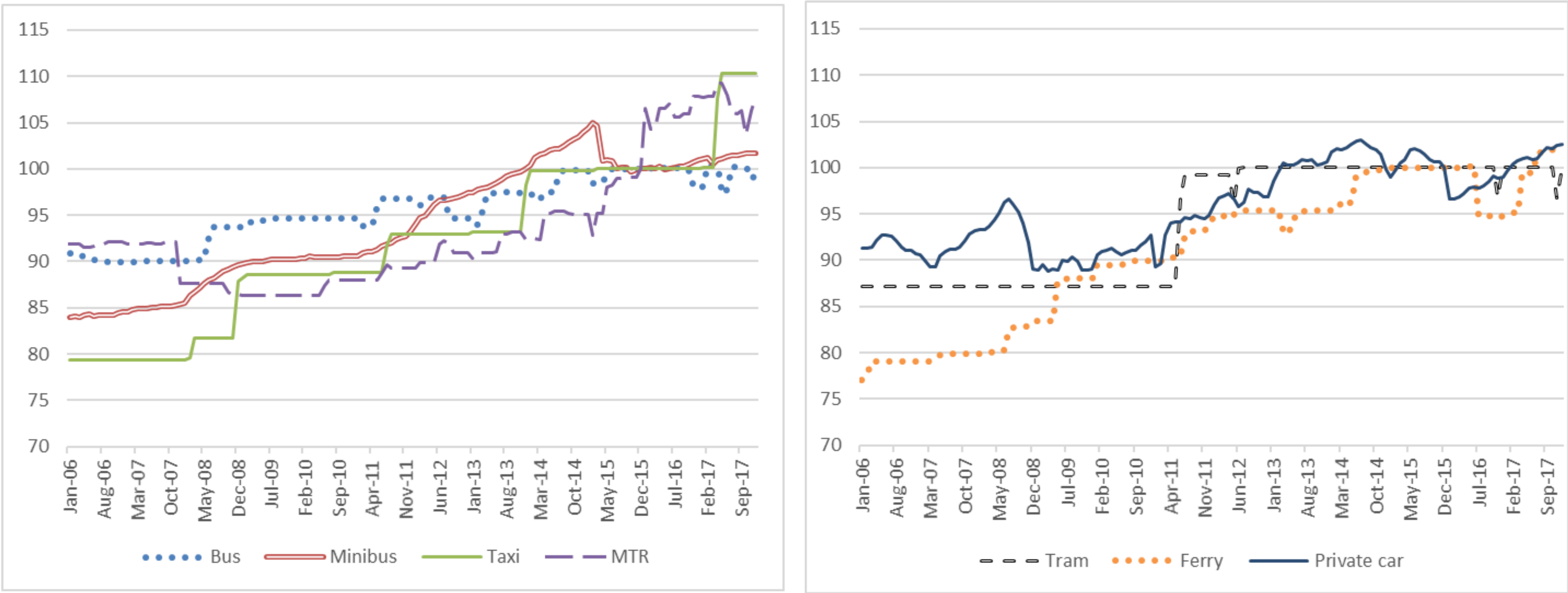

Fig. 3. Hong Kong's monthly transportation price indices for the 12-year period of January 2006 - December 2017