URBAN RAIL TRANSIT AND GREEN URBANISATION

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1 INTRODUCTION

The COVID-19 pandemic and the resulting lockdowns forced many advanced economies into an unintentional experiment wherein a significant portion of their workforce had to adapt to remote work. As employees around the world tend to acclaim the benefits of remote working, this mass work-from-home experiment has triggered a debate about the future of work. Consequently, there have also been speculations about the potential demise of traditional office setups, thereby putting into question the future of dense urban centres, that is, cities (Althoff, Eckert, Ganapati, & Walsh, 2022; Florida, Rodriguez-Pose, & Storper, 2021). Such conjectures have created a greater need to understand the benefits of densification for society and the economy at large.

There now exists a large volume of research dedicated to understanding the impact of densification on productivity and innovation. The weight of the evidence suggests that cities and industrial clusters have strong positive statistical associations with the economic performance of firms and workers [see (Graham & Gibbons, 2019) for a detailed review]. Interestingly, an emerging strand in the literature has also focused on evaluating the climate change impacts of densification. For instance, using data from the UK, a recent study showed that large cities are more efficient than small towns in terms of energy consumption and waste generation, thus providing compelling evidence in support of *green urbanization* (Eeckhout & Hedtrich, 2021). The energy demanded by the transport sector remains a key theme of interest in such studies given that it constitutes approximately 30 percent of global energy consumption and 20 percent of greenhouse gas emissions, thereby being a significant contributor to climate change (Seto, et al., 2021). While the existing literature looks into transport energy requirements in general, there remains a critical knowledge gap in our understanding of this impact across various travel modes. We contribute to this line of research by assessing how densification affects the energy usage of two major modes of day-to-day transport in cities: urban rail transit (metro) and road-based private vehicular travel.

We first study the impact of densification on the energy usage of metro systems, commonly recognized as a key pillar of sustainable transport in cities. There is now a great deal of evidence suggesting that metro operations with a high density of usage are highly productive and cost-efficient, thus highlighting key aspects of their economic sustainability (Anupriya, Graham, Carbo, Anderson, & Bansal, 2020). However, evidence of their environmental sustainability, particularly in terms of their energy use efficiency remains limited. To address this gap in the literature, we develop a novel model, guided by the theory of production in economics, to study the energy usage of transport operations. The objective is to assess how operational density, that is, the total passenger kilometers travelled on a given network, affects the relative demand for energy in metro operations. The model is constructed using a unique and high-quality panel dataset of twenty-seven metro systems around the world. The data has been collected by the Transport Strategy Centre (TSC) at Imperial College London since 1994. It is worth emphasizing that estimating the relationship of interest is not straightforward due to confounding biases that emerge via the complex interactions between operational density, energy usage and the unobserved productivity of the metro firm. To adjust for such biases, we adopt a causal inference approach based on dynamic panel generalized method of moments (DPGMM) estimation.

Next, we comprehend the impact of densification on the energy usage of private vehicular operations on urban road networks. Contrary to metros, urban road networks with a high density of usage have, on an average, been found to be less productive and cost-efficient due to technical inefficiencies resulting from increased congestion (Loder, Ambuhl, Menendez, & Axhausen, 2019; Couture, Duranton, & Turner, 2018). It will be interesting to see whether such effects transpire in their energy-use efficiency too. We investigate how operational density affects the relative demand for energy in road-based private car travel. The model of interest is developed using the Millennium Cities database for sustainable transport compiled by the International Association of Public Transport (UITP) and application of a pooled ordinary least squares (POLS) estimation.

The paper proceeds as follows. Section 2 describes the model and the data used in this study. Section 3 lays out our results. Conclusions are drawn in the Section 4.

2 MODEL AND DATA

This section has three subsections. The first subsection describes the theoretical framework, followed by details of the empirical model and its estimation in the next subsection. The final subsection describes the data used in the empirical analysis.

Theoretical Framework

We have the short-run variable cost function CV_{it}^{s} for a transport operation i at time t, represented as:

$$CV_{it}^{s} = f(y_{it}, N_{it}, \boldsymbol{w}_{it}, \omega_{it}) \tag{1}$$

where y and N are measures of output (passenger-kilometres) and network size (operated route length), respectively. $\boldsymbol{w}$ is a vector of prices for variable inputs: labour and energy. ω is the unobserved productivity of the operation. According to economic theory, the conditional factor share equations for input j, x_j can be derived from the short-run costs CV_{it}^{s} using Shepherd's lemma (the firm-year subscripts have been dropped for notational simplicity) as follows (Shepherd, 2015):

$$\frac{\partial\, CV^{s}(y,\boldsymbol{w},N,\omega)}{\partial\, w_j} = x_j \tag{2}$$

Thus, requirement of input j by operation i at time t, $x_{j,it}$, can be represented as:

$$x_{j,it} = g(y_{it}, N_{it}, \boldsymbol{w}_{it}, \omega_{it}) \tag{3}$$

Model Specification and Empirical Estimation

Following from equation 3, the transport energy consumption equation can be represented using a flexible functional specification with second-order terms as follows:

$$\begin{aligned}\log E_{it} = \alpha_0 + \alpha_y \log y_{it} + \sum_{j=1}^{2} \alpha_j \log w(j)_{it} + \alpha_N \log N_{it} + \beta_{yy} \log y_{it}^2 \\ + \sum_{j=1}^{2} \beta_{jy} \log y_{it} \log w(j)_{it} + \beta_{yN} \log y_{it} \log N_{it} \\ + \sum_{j=1}^{2} \sum_{k=1}^{2} \beta_{jk} \log w(j)_{it} \log w(k)_{it} + \sum_{j=1}^{2} \beta_{jN} \log w(j)_{it} \log N_{it} + \beta_{NN} \log N_{it}^2 \\ + \delta_t + \omega_{it} + \epsilon_{it}\end{aligned} \tag{4}$$

where δ_t are year dummies that capture the year-specific effects and ϵ_{it} is a normally distributed random error term.

From equation 4, the key estimand of interest that captures the impact of densification, or equivalently, the intensity of use of the transport network on the operational energy requirement can be determined as follows:

$$e_{it}^{E} = \frac{\partial \log E_{it}}{\partial \log y_{it}} = \alpha_y + 2\beta_{yy} \log y_{it} + \sum_{j=1}^{2} \beta_{jy} \log w(j)_{it} + \beta_{yN} \log N_{it} \tag{5}$$

Note that there are operational factors such as managerial efficiency or firm productivity in the case of a metro operation, or technical efficiency related to driver's behaviour or vehicular characteristics in the case of road-based private car travel, which play an important role in determining the quantity of energy consumed in the production of a given level of output. The unavailability of a measure ω_{it} for these factors may lead to a confounding bias in the parameter estimates of the energy consumption model, commonly known as omitted variable bias. To adjust for such confounding biases, we adopt a causal statistical approach to estimate equation 4, which is based on instrumental variables estimation. In particular, we use a vector of time-varying instrumental variables (IVs), that are strongly correlated with the confounded covariates of the model, but do not directly determine the dependent variable of the model. In the absence of suitable external IVs, relevant IVs can be derived from the panel nature of the dataset. Lagged levels of confounded covariates can be used as their instruments for differenced equations. If the dataset is highly persistent, additional moment conditions are generated for estimation by adding lagged first differences of covariates as instruments in the levels equation. The parameter estimates of the model are obtained via application of dynamic panel generalised method of moments (DPGMM) estimation.

We emphasize at this point that the Millennium Cities database for sustainable transport used for estimation of the energy model for road-based private-vehicular travel only comprises the cross-sectional dimension, thereby hindering our ability to derive appropriate IVs from the longitudinal nature of the dataset. We, therefore, estimate this model via a pooled ordinary least squares (POLS) estimation.

Data

To study the energy usage of metro operations, we make use of data that has been collected by a consortium of metro operators, namely the Community of Metros, managed by the Transport Strategy Centre. The consortium focuses on benchmarking using an extensive dataset comprising key performance indicators related to 44 metro operations in 40 cities around the world. However, the dataset has several missing values depending upon the extent of information reported by the metro operator each year. Accordingly, we obtain an unbalanced panel dataset with 174 observations consisting of 27 systems over 15 years, between 2006 and 2019. Due to the sensitive commercial nature of the data, we present our results in an anonymised form.

The energy consumption model for private vehicular operation on urban road networks is estimated using cross-sectional data from the Millennium Cities Database for Sustainable Transport (1999) compiled by UITP. The database contains information on 100 cities from around the world for the year 1995. From these, 84 cities were used for the estimation of the model as data for some cities were incomplete. These 84 cities come from 42 different countries. The cross-sectional nature of the data increases the potential for omitted variable bias in regression modelling. That said, one of the guiding principles in establishing the Millennium Cities Database was to achieve a high level of data consistency. Furthermore, the problem we address in this paper requires a good range of variation in density, which is generally not available in time-series data as density is highly persistent. We know of no panel data set with a sufficiently wide cross-section at the city level.

3 RESULTS AND DISCUSSION

This section has three subsections. The first subsection discusses the estimates of the energy consumption model (equation 4), which is followed by a detailed discussion of the energy-use efficiency estimates in the section subsection.

The estimated energy consumption models

The estimated elasticity of energy consumption with respect to different covariates for metro operations (equation 4) are reported at mean values of the data. The elasticity estimate with respect to output suggests that if the use of factors associated with density increases by 10%, the energy consumed by metro operations increases by 6.65% only.

Table 1: The estimated energy consumption model for metro operations.

	Total Energy		
Covariate	Coefficient	Std. Error	p-value
Elasticity w.r.t. output	0.665	0.060	0.000
Elasticity w.r.t. network size	0.252	0.091	0.006
Elasticity w.r.t. labour price	0.061	0.064	0.345
Elasticity w.r.t. energy price	-0.152	0.076	0.045
No. of Observations	201		
No. of Instruments	180		

The estimated energy elasticity of energy consumption with respect to output suggests for road based private vehicular operations that if the use of factors associated with density increases by 10%, the energy consumed by private vehicular operations increases by 9.26%.

Table 2: The estimated energy consumption model for road-based private vehicular operations

Covariate	Coefficient	Std. Error	p-value
No. of Observations	86		
Adjusted R-squared	0.980		
Elasticity w.r.t. output	0.926	0.053	0.000
Elasticity w.r.t. network size	0.135	0.060	0.024
Elasticity w.r.t. labour price	-0.159	0.051	0.002
Elasticity w.r.t. energy price	-0.258	0.050	0.000

The estimated energy-efficiency

To further understand the energy-efficiency of the two modes, we discuss the elasticity estimates of unit energy consumption, that is, energy consumption per unit passenger-kilometer, with respect to output (measured in passenger kilometers). Note that while the elasticity estimate for metro operations is statistically significant at the 95% confidence level, the estimate for road-based private vehicular operations is statistically insignificant.

Table 3: The estimated unit energy consumption elasticities at mean levels of the data.

Mode	Coefficient	Std. Error	95% Confidence Interval	
Urban rail transit	0.335	0.060	0.217	0.454
Private vehicular travel	0.074	0.053	-0.030	0.179

4 CONCLUSIONS

Our analysis suggests that while densification of rail transit operations substantially reduces its energy requirement per unit output, increasing private vehicular operations on road networks offers no energy benefits. These results underscore that a compact urban form, primarily driven by rail-based travel, can lead to a greener future.

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