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Spatial economic dynamics in transport project appraisal☆

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ABSTRACT

Major transport projects can alter the distribution of population and employment as households and firms respond to changes in accessibility. These land use changes can affect the distribution and scale of benefits delivered. However, models used in transport project appraisal often assume fixed land uses. A dynamic spatial model (DSM) of the economy can quantify land use changes and the level and spatial distribution of welfare impacts resulting from changed travel times. Effects of project expenditures, funding and financing are also accounted for.

This paper presents a DSM featuring internal migration, commuting and trade, and an illustrative application to a hypothetical rail upgrade in South East Queensland, Australia. Internal migration proves critical to the distribution of benefits within and beyond the metropolitan region. Travel time changes are exogenous in the simulation, but linking the DSM to a conventional transport model would enable a comprehensive account of land use–transport interactions.

1. Introduction

Australia is seeing record spending on public infrastructure projects, especially on transport mega-projects (Terrill et al., 2020; Infrastructure Australia, 2021). This trend is not unique. For example, London, New York, and Paris have pursued ambitious transportation initiatives like Crossrail, the Second Avenue Subway, and the Grand Paris Express. Governments are often keen to emphasise the potential of such projects to 'reshape' cities. It is surprising then that the impacts of transport projects on land use are not routinely or consistently accounted for when estimating their economic benefits. This is concerning because land use changes have implications for the estimation of both conventional and wider economic benefits of transport projects. They can also have broader policy implications. Given changes in travel times characterising the operational phase of a project, I show that a dynamic spatial model (DSM) of the economy featuring internal migration, trade, and commuting can be used to quantify: (i) dynamic land use changes; and (ii) the level and spatial distribution of welfare impacts. The effects of construction and maintenance activities, and project financing and funding, can also be quantified in this framework.

It has long been recognised that transport costs affect land uses and *vice versa*. Quantitative modelling of such land use–transport interactions (LUTI) dates back to Lowry (1964). A diverse range of modelling approaches and models have since been developed (Hunt et al., 2005). In some cases, operational LUTI models have been applied in transport project appraisals.[1] Unfortunately, such applications remain exceptions to the usual practice, which is dominated by the use of four-step transport to estimate benefits (McNally, 2007). These transport models take land use as given, an assumption that is hard to justify, given now abundant evidence that major road and rail investments are likely to have significant long-run impacts on residential population and/or jobs (Kasraian et al., 2016; Xie and Levinson, 2010; Levinson, 2008; Costa et al., 2021; Baum-Snow, 2007; Duranton and Turner, 2012, 2011; Iacono and Levinson, 2016).

Recent interest in land use impacts of transport projects has focused on 'wider economic benefits' (WEBs), particularly local and urban agglomeration effects (Vickerman, 2008). More fundamentally, land use is the basis for estimating transport demands. Failing to consider changes in land use may bias estimation of user benefits. In a simulation study, Eliasson et al. (2020) find that the optimal composition of a large portfolio of small metropolitan transport projects is quite robust to the omissions of land use change. However, they note these findings may not transfer to decisions on large projects. Vickerman (2008) stresses that it is not the size but the context of a project within a transport network that determines the relative importance of land use change. Land use change and spatial economic interactions are also central to the spatial distribution of benefits (Bröcker et al., 2010), a point on which I focus in this paper. Finally, beyond the confines

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[1] Recent examples in the Australian context include KPMG (2021), Le et al. (2021)

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of cost–benefit analyses, land use changes may have broader policy relevance (Waddell, 2011).

In this paper, I present a dynamic spatial model (DSM) of the Australian economy and use it to assess the costs and benefits of a hypothetical urban transport project. Spatial equilibria are central to the land use component(s) of those LUTI modelling approaches that Wegener (2021) classifies as spatial interaction location models (as opposed to accessibility-based location models). In particular, DSMs have much in common with spatial computable general equilibrium (SCGE) models (Anas and Liu, 2007; Robson et al., 2018), emphasising interactions in a set of interconnected land, labour and product markets. However, unlike comparative static or recursive dynamic SCGE models, agents in DSMs make forward-looking decisions. That is important for two reasons. Firstly, many responses associated with land use changes (e.g. residential relocation) entail large financial or non-financial costs, which motivate forward-looking behaviour. Secondly, the structure of DSMs provides a clear theoretical basis for estimating the welfare impacts of a project and their distribution within the current population.

DSMs have mainly been applied to questions of economic geography concerning migration and trade between states within countries as in Caliendo et al. (2019)—henceforth, CDP—or between countries (e.g. Caliendo et al., 2021). Balboni (2021) models effects of climate change on inter-regional transport infrastructure in Vietnam. In the urban context, regional labour markets are connected dynamically via migration flows and contemporaneously via commuting flows. Warnes (2022) develops a DSM of Buenos Aires to study the differential effects of transport infrastructure on high- and low-skilled residents. I treat commuting similarly but model workers making choices amongst occupations and locations. I also model multiple industries, thus allowing for differences in their spatial distributions and for more nuanced interactions through labour and product markets. Finally, I allow for productivity spillovers dependent on effective job densities, as is standard in urban spatial models (see e.g. Ahlfeldt et al., 2015; Tsivanidis, 2021).

One barrier to the operational adoption of LUTI modelling has been the complexity and data requirements of many models (Hunt et al., 2005). While the DSM I present involves a very large number of variables, it has a clear and relatively simple theoretical structure. The model operates at a national scale. I construct a master database for Australia relying only on Census and other publicly available datasets. However, to facilitate computational solution of the model, spatial units, occupations and industries are flexibly aggregated as relevant to a particular application. This approach echoes that often used in multiregional computable general equilibrium modelling (Wittwer, 2012).

I apply the DSM to assess the introduction of a hypothetical fast express passenger rail service in the South East Queensland (SEQ) region of Australia, which includes the cities of Brisbane and the Gold Coast. For this purpose, I aggregate the model database to distinguish 354 localities within the SEQ region and 100 larger regions in the rest of Australia. I distinguish three occupational groups, five industries and a housing sector. The project is represented by changes in transport costs, a schedule of construction, operating and maintenance costs, and a stylised but macroeconomically consistent representation of finance and funding. In the simulation, changes in transport are exogenous. However, in the discussion, I consider how the DSM could be coupled with a four-step transport model to constitute a dynamic LUTI model.

The simulation results feature changes in land use that unfold over several decades. Land use changes are largest around rail stations, but small changes throughout the SEQ region and beyond are cumulatively significant. The model's forward-looking behaviour results in some land use change in advance of expected accessibility gains. However, because of its limited duration, the construction phase predominantly affects the locations of jobs rather than residential locations.

Large welfare gains accrue to those initially residing near the stations served by the project. That is before accounting for the fact that many of these residents will also own local property. Small but cumulatively significant gains are widely distributed within and beyond the SEQ region. Migration costs are crucial to the spatial diffusion of welfare gains and to the distribution of gains between residents and property owners. For blue-collar workers in the most directly affected labour markets, economic effects associated with construction activities also play a role. The sources of project funding may significantly alter the distribution of net benefits. From a normative perspective, broad diffusion of benefits provides one justification for significant national co-funding of projects undertaken by state or metropolitan governments.

The structure of this paper is as follows. In Section 2, I present the full set of model equations. The model is ultimately formulated and solved using the 'exact hat algebra' of CDP. I show how key equations (for migration, commuting and spillovers) can be rewritten in terms of the changes in variables from one period to the next. In 3, I outline the procedures used to construct an economic database, to calibrate, estimate or otherwise specify the model's behavioural parameters, and to estimate transport costs. In Section 4, I describe the solution algorithm and the construction of baseline and project case scenarios. The latter is characterised by changes in generalised travel costs and a series of capital and operating expenditures. Simulation results are presented in Section 5. In Section 6, I first discuss the strengths and limitations of a DSM-based analysis of project costs and benefits. I then discuss how a DSM model could be linked with a four-step transport model to enable a comprehensive LUTI-based analysis. Section 7 provides concluding remarks.

2. Model

DSM models embed an infinite-horizon, dynamic discrete choice model based on random utility theory within a dynamic spatial general equilibrium framework. I distinguish N spatial units in the national economy in which people may reside and/or work, J sectors and O occupations. Spatial units are indexed by r or s, sectors (which I use interchangeably with industries or the goods or services they produce, including housing) by i or j, and occupations by k or l. Time is discrete and indexed $t = 0, 1, 2, \dots$. The economy is populated by profit-maximising firms and forward-looking, utility-maximising households.

Within each sector, firms produce goods or services using a Cobb–Douglas technology with constant returns to scale. They demand intermediate inputs, occupational labour and a local fixed factor, which I will refer to as land, as in CDP. Firms in the first $J - 1$ sectors produce goods or services that can be traded both between spatial units and internationally. Trade is shaped by spatial frictions, which I associate with freight costs for goods, and business or private travel costs for intermediate or final services. In the Jth sector, non-tradable housing services are produced using only intermediates and land.

Each household is endowed with one unit of labour per period. At the beginning of each period, a worker–household chooses her occupation and place of residence. Switching occupation and/or residence may entail large pecuniary and/or psychic costs. As in CDP, I assume these costs are time-invariant. She then chooses a place of work, taking into account spatial differences in occupational wage rates and commuting costs. During the period, she supplies her unit of occupational labour at her work location. In her residential location, she consumes housing and tradable goods and services

For computational tractability of the model, I assume that a worker in a given occupation and location is indifferent to her industry of employment. That is, firms in all industries participate in the same local occupational labour markets. This is consistent with growing evidence that occupational switching costs are much larger than industry switching costs (Bartik and Rinz, 2018). Tractability also motivates the splitting of the discrete choice problem into two stages. Given a lack of explicit dynamics in workplace choices, simulating with time periods of several years duration is probably most appropriate.

The government sector is not explicitly represented, although I do represent a wide variety of direct and indirect taxes (and subsidies). Government transfers in kind to households (e.g. much healthcare and education provision) and even public goods (e.g. public order) are represented as subsidies to household consumption. For simplicity, public goods (e.g. defence) are treated similarly. The advantage of this is that the spatial distribution of consumption demands follows from the spatial distribution of households and household income. Investment and export demands are treated differently, as described below.

2.1. Workplace choices

A household's indirect flow utility function in occupation k, residence r, and workplace s at time t is

$$\mathrm{u}_t^{krs} = \epsilon_{\mathrm{u}_t}{}^{krs} \frac{m_t^{krs}}{\mathcal{P}_t^r D_t^{rs}}, \tag{1}$$

where for the predetermined (k, r), $\epsilon_{1_t}{}^{krs}$ are individual-specific shocks associated with workplace choice, m_t^{krs} is after-tax income and D_t^{rs} reflects the dis-utility of commuting. The local consumption price index faced by all local households resident in r is $\mathcal{P}_t^r$.

For tractability, I assume that each worker receives gross non-wage income in proportion to her wage income. However, I allow that taxes on wage and non-wage income may potentially differ by place of residence. After-tax disposable income is given by

$$m_t^{krs} \equiv \left(\tau_{\mathrm{L}_t}{}^r + \tau_{\mathrm{K}_t}{}^r Y_t\right) w_t^{ks}, \tag{2}$$

where w_t^{ks} is the local occupational wage rate, $\tau_{\mathrm{L}_t}{}^r$ and $\tau_{\mathrm{K}_t}{}^r$ are income tax powers[2] for wage and non-wage income respectively and Y_t is the endogenously determined economy-wide ratio of non-wage income (net of retained earnings, which fund investment) to wage income.

I assume a Cobb–Douglas sub-utility function for consumption for all households, so the ideal price index for consumption in each spatial unit is

$$\mathcal{P}_t^r = \prod_{i=1}^{J} \left(\frac{\tau_{\mathrm{C}_t}{}^{ir} P_t^{ir}}{\alpha_{\mathrm{C}}^{ir}} \right)^{\alpha_{\mathrm{C}}^{ir}}, \tag{3}$$

with

$$\sum_i \alpha_{\mathrm{C}}^{ir} = 1. \tag{4}$$

The $\tau_{\mathrm{C}_t}{}^{ir}$ are consumption tax (or subsidy) powers and P_t^{kr} are local delivered prices of tradable goods and services or the price of (non-tradable) housing services. Given the assumed form of the sub-utility function, household expenditure shares on goods and services are equal to α_{C}^{ir}.

I assume that the workplace shocks $\epsilon_{\mathrm{u}_t}{}^{krs}$ are drawn from an i.i.d. Fréchet distribution with shape parameter ε_k. The expected flow utility associated with an occupation–residence pair before drawing an individual workplace shock is given by

$$U_t^{kr} = \left(\sum_s \left(\frac{m_t^{krs}}{\mathcal{P}_t^r D_t^{rs}} \right)^{\varepsilon_k} \right)^{1/\varepsilon_k}. \tag{5}$$

The inclusive value U_t^{kr} summarises the *ex ante* attractiveness of each occupation–residence pair and so features in the solution of the household's dynamic problem in the next section.

Integrating over individuals yields commuting destination probabilities conditional on place of residence (for details of the more general static location choice problem, see e.g. Ahlfeldt et al., 2015). For workers in occupation k and residence r, the probability of commuting to workplace s in period t is given by

$$\psi_t^{krs} = \left(\frac{w_t^{ks} D_t^{rs}}{U_t^{kr}} \right)^{\varepsilon_k}. \tag{6}$$

I can then calculate the average wage of a resident worker as

$$W_t^{kr} = \sum_{s=1}^{N} \psi_t^{krs} w_t^{ks}. \tag{7}$$

From (2), the average income of occupational workers by place of residence is then

$$M_t^{kr} = \left(\tau_{\mathrm{L}_t}{}^r + \tau_{\mathrm{K}_t}{}^r Y_t\right) W_t^{kr} \tag{8}$$

2.2. Internal migration and occupational choices

Given an occupation–residence pair (k, r) in period t, the household's lifetime utility is given by the Bellman equation

$$\mathrm{v}_t^{kr} = \ln U_t^{kr} + \max_{\{l,q\}_{l=1,q=1}^{O,N}} \left\{ \beta\, \mathbb{E}\left[\mathrm{v}_{t+1}^{lq}\right] + \zeta^{kr,lq} + \nu\, \epsilon_{\mathrm{v}_t}{}^{lq} \right\}. \tag{9}$$

That is, the expected flow utility in the current state, plus the expected continuation value from the optimal choice of the next state discounted by β. Deterministic switching costs are denoted by $\zeta^{kr,lq}$ and individual-specific dynamic shocks by $\epsilon_{\mathrm{v}_t}{}^{lq}$. As is standard in DSMs, I assume these shocks are distributed i.i.d. in time following a zero-mean Gumbel distribution with shape parameter ν (see e.g. CDP).[3] Then, integrating over households' dynamic preference shocks, one obtains

$$V_t^{kr} = \ln U_t^{kr} + \nu \log \left(\sum_{l=1}^{O} \sum_{q=1}^{N} \exp\left(\beta V_t^{lq} + \zeta^{kr,lq}\right) \right). \tag{10}$$

As shown in CDP, the share of (k, r) households switching to (l, q) is given by

$$\mu_t^{kr,lq} = \frac{\exp\left(\beta V_{t+1}^{lq} - \zeta^{kr,lq}\right)^{1/\nu}}{\sum_{l'=1}^{J} \sum_{q'=1}^{N} \exp\left(\beta V_{t+1}^{l'q'} - \zeta^{kr,l'q'}\right)^{1/\nu}}. \tag{11}$$

Evolution of the resident labour force from one period to the next is given by

$$H_t^{lq} = \sum_{i=k}^{O} \sum_{r=1}^{N} \mu_{t-1}^{kr,lq} H_{t-1}^{kr}, \tag{12}$$

and the number of jobs in each occupation and work location is given by

$$L_t^{ks} = \sum_{r=1}^{N} \psi_t^{krs} H_t^{kr}. \tag{13}$$

2.3. Firms, product and housing markets

A variety of tradable intermediate goods or services are produced by monopolistically competitive firms operating within each sector. These firms' production requires labour, land, and intermediate inputs. The goods and services consumed by both firms and households are composites of traded intermediate varieties. Each variety is sourced from the region that can deliver it at least cost. For simplicity, trade costs have the standard iceberg form, i.e. they are paid for in units of the product supplied. Goods and services are not only traded within Australia, but are imported and exported.

[2] I define tax powers as one less the tax rate.

[3] Note that idiosyncratic shocks in the dynamic problem are more important, relative to deterministic factors, the larger the value of ν. In the static sub-problem, they are more important the smaller the value of ε_k.

Firms' unit costs are given by

$$p_t^{ir} = \left(A_t^{ir}\right)^{-\alpha_{\mathrm{V}}^i} \left(\frac{\tau_{\mathrm{K}t}^{\ ir} r_t^{ir}}{\alpha_{\mathrm{K}}^i}\right)^{\alpha_{\mathrm{K}}^i} \prod_{k=1}^{O} \left(\frac{\tau_{\mathrm{L}t}^{\ ir} w_t^{kr}}{\alpha_{\mathrm{L}}^{ikr}}\right)^{\alpha_{\mathrm{M}}^{ikr}} \prod_{i=1}^{J-1} \left(\frac{\tau_{\mathrm{M}t}^{\ ijr} P_t^{jr}}{\alpha_{\mathrm{M}}^{ij}}\right)^{\alpha_{\mathrm{M}}^{ij}}, \tag{14}$$

where the sector average level of productivity A_t^{ir} will be further specified below, the rental price of land is r_t^{ir}, and input tax powers[4] on land, labour and intermediates are $\tau_{\mathrm{K}t}^{\ ir}$, $\tau_{\mathrm{L}t}^{\ ir}$ and $\tau_{\mathrm{M}t}^{\ ijr}$ respectively. Given limitations of sub-national datasets, I assume that the Cobb–Douglas exponents are independent of region, except those for the different types of occupational labour. The coefficients on inputs sum to one. These correspond to firms' (tax-inclusive) input cost shares. For convenience, I denote the cost share for value-added as

$$\alpha_{\mathrm{V}}^i \equiv \alpha_{\mathrm{K}}^i + \sum_{k=1}^{O} \alpha_{\mathrm{L}}^{ikr}. \tag{15}$$

As is common in urban economic models, I make sector average productivity a function of effective job density. As suggested by empirical findings (Groot and de Groot, 2020), I assume that only higher-skilled workers contribute to these productivity spillovers. I take these to be workers in the first $O_{\mathrm{H}} < O$ occupations. Thus, productivity is given by

$$A_t^{ir} = \bar{A}^{ir} \left(\sum_{s=1}^{N} \sum_{k=1}^{O_{\mathrm{H}}} \exp\left(-\varrho g_t^{rs}\right) L_t^{ks}\right)^{\chi_i} \tag{16}$$

where $\bar{A}^{ir}$ captures differences in location-specific, time-invariant fundamentals, ϱ is a distance-decay factor, and χ_i is the elasticity of productivity to effective high-skilled job density.

The cost of composite goods is given by

$$P_t^{is} = \Gamma^{is} \left(\sum_{r=1}^{N+1} \left(\frac{p_t^{ir} d_t^{irs}}{\left(A_t^{ir}\right)^{\alpha_{\mathrm{V}}^i}}\right)^{-\theta^i}\right)^{-1/\theta^i} \tag{17}$$

where $d_t^{irs} \geq 1$ are iceberg trade costs, θ^i are shape parameters for the distribution of firm-specific productivity levels and Γ^{is} are constants related to the distribution.[5]

Prices of imported goods and services in domestic currency (f.o.b.) are equal to

$$p_t^{i,N+1} = p_{\mathrm{F}t}^{\ i}/e_t, \quad r = N+1 \tag{18}$$

where $p_{\mathrm{F}t}^{\ i}$ are exogenous foreign prices and e_t the exchange rate (expressed as units of foreign currency per unit of domestic currency). In the simulations reported below, foreign prices are held constant, but the exchange rate adjusts to satisfy an exogenously specified trade balance in each period. Foreign prices are held constant. I do not allow for import duties in the model given that the rates are generally low in Australia. However, the modelled trade frictions may incorporate various border costs, e.g. phytosanitary controls.

The share of goods or services sourced from each region is given by

$$\pi_t^{irs} = \frac{\left(p_t^{ir} d_t^{irs}/\left(A_t^{ir}\right)^{\alpha_{\mathrm{V}}^i}\right)^{-\theta^i}}{\sum_{r'=1}^{N+1} \left(p_t^{ir'} d_t^{ir's}/\left(A_d^{ir'}\right)^{\alpha_{\mathrm{V}}^i}\right)^{-\theta^i}}. \tag{19}$$

As in Kleinman et al. (2021)—henceforth KLR—I model the production of housing services as a special case in which (i) no labour is used; (ii) there are no spillovers; and (iii) trade costs are infinite. Note also that housing services are consumed only by households.

[4] I define tax powers on inputs as one plus the tax rate.

[5] For a detailed exposition of the theory underlying the model of production and trade, see CDP and works cited therein. In the final, time-differenced formulation of the model, the constant Γ^{is} will cancel out.

2.4. Market clearing

For each good or service, market clearing requires that

$$Y_t^{ir} = \sum_{s=1}^{N+1} \pi_t^{irs} X_t^{is} \tag{20}$$

where Y_t^{ir} is the value of industry output in each spatial unit (or imports for $r = N+1$) and X_t^{is} is the combined value of intermediate, investment and final demands in each spatial unit (or exports for $r = N+1$) at market prices.

Aggregate local demands ($r = 1, \ldots, N$) are equal to

$$X_t^{ir} = \sum_{j=1}^{J} \frac{\alpha_{\mathrm{M}}^{ij} Y_t^{jr}}{\tau_{\mathrm{M}t}^{\ ijr}} + \frac{\alpha_{\mathrm{I}}^i I_t^r}{\tau_{\mathrm{I}t}^{\ ir}} + \sum_{k=1}^{O} \frac{\alpha_{\mathrm{C}}^{ir} M_t^{kr} H_t^{kr}}{\tau_{\mathrm{C}t}^{\ ir}}. \tag{21}$$

As I do not model the accumulation of capital, matching the data requires either reclassifying investment demands as consumption (as in CDP) or specifying investment demands exogenously. I opt for the latter approach for two reasons. Firstly, I intend ultimately to extend the present model to incorporate the accumulation of fixed capital, as in KLR. Secondly, distinguishing investment demands provides a natural way to specify public investments in transport infrastructure, which will be a key component of the simulation presented below. I exogenously specify aggregate local investment I_t^r and assume these investment goods are produced using a common Cobb–Douglas technology with parameters α_{I}^i. Input tax powers on investment are $\tau_{\mathrm{I}t}^{\ ir}$.

The market value of exports ($r = N+1$) responds to f.o.b. prices in foreign currency

$$X_t^{ir} = E_0^{ir} \left(e_t \tau_{\mathrm{X}t}^{\ i}\right)^{-\theta_i} \left(P_t^{ir}\right)^{1-\theta_i}. \tag{22}$$

where E_0^{ir} are constants reflecting the initial prices and market value of exports and $\tau_{\mathrm{X}t}^{\ i}$ are taxes on exports.[6]

For local labour markets, market clearance requires

$$w_t^{kr} L_t^{kr} = \sum_{i=1}^{J} \frac{\alpha_{\mathrm{M}}^{ikr} Y_t^{ir}}{\tau_{\mathrm{L}t}^{\ ir}}, \tag{23}$$

while for land markets, the condition is simply

$$r_t^{ir} N_t^{ir} = \frac{\alpha_{\mathrm{K}}^i Y_t^{ir}}{\tau_{\mathrm{K}t}^{\ ir}}. \tag{24}$$

2.5. Taxation, transfers and the distribution of land rents

Total net revenue from taxes (and subsidies) on intermediate inputs, investment, consumption and exports is

$$\begin{aligned}\mathcal{R}_{\mathrm{C}t} = \sum_{i=1}^{J} \Bigg[\sum_{r=1}^{N} \Bigg(\sum_{j=1}^{J} \frac{\tau_{\mathrm{M}t}^{\ ijr} - 1}{\tau_{\mathrm{M}t}^{\ ijr}} \alpha_{\mathrm{M}}^{ij} Y_t^{jr} + \frac{\tau_{\mathrm{I}t}^{\ ir} - 1}{\tau_{\mathrm{I}t}^{\ ir}} \alpha_{\mathrm{I}}^i I_t^r \\ + \sum_{k=1}^{O} \frac{\tau_{\mathrm{C}t}^{\ ir} - 1}{\tau_{\mathrm{C}t}^{\ ir}} \alpha_{\mathrm{C}}^{ir} M_t^{kr} H_t^{kr} \Bigg) + \left(\tau_{\mathrm{X}t}^{\ i} - 1\right) X_t^{i,N+1} \Bigg].\end{aligned} \tag{25}$$

Total net revenue from factor input taxes (and subsidies) is

$$\mathcal{R}_{\mathrm{F}t} = \sum_{r=1}^{N} \sum_{i=1}^{J} \left(\frac{\tau_{\mathrm{L}t}^{\ ir} - 1}{\tau_{\mathrm{L}t}^{\ ir}} \left(\sum_{k=1}^{O} \alpha_{\mathrm{L}}^{ikr}\right) + \frac{\tau_{\mathrm{K}t}^{\ ir} - 1}{\tau_{\mathrm{K}t}^{\ ir}} \alpha_{\mathrm{K}}^i \right) Y_t^{ir}. \tag{26}$$

Total gross revenue from taxes on household income is

$$\mathcal{R}_{\mathrm{H}t} = \sum_{r=1}^{N} \left(1 - \tau_{\mathrm{L}t}^{\ r} + \left(1 - \tau_{\mathrm{K}t}^{\ r}\right) Y_t\right) \omega_t^{kr}. \tag{27}$$

The ratio of non-wage to wage income is

$$Y_t = \frac{\mathcal{R}_{\mathrm{C}t} + \mathcal{R}_{\mathrm{F}t} + \mathcal{R}_{\mathrm{H}t} - B_t + \sum_{r=1}^{N} \left(\sum_{i=1}^{J} r_t^{ir} N_t^{ir}\right) - I_t^r}{\sum_{r=1}^{N} \sum_{k=1}^{O} w_t^{kr} L_t^{kr}}. \tag{28}$$

[6] These include indirect taxes paid on goods and services by international visitors.

where the term B_t represents the net outflow of income abroad. I simply identify this with the balance of trade and exogenise it by making e_t endogenous. This firstly allows us to account for the trade imbalance in the data. Secondly, I can change B_t in the simulation of a transport project to reflect initial foreign borrowing to finance the project, followed by interest repayments.

2.6. Exact hat form

A central difficulty in modelling migration and trade is that transition costs and spatial frictions are difficult to observe. However, migration and trade flows are more easily observed. By reformulating their model in terms of ratios of variables at $t+1$ to t, CDP show that unobservable, time-invariant migration costs cancel out, as do trade costs. Assuming relative changes in trade costs are observed, trade costs may be time-varying. They refer to this model formulation in ratios as 'dynamic hat algebra'.[7] In this Section I present the equations relating to dynamic choices, commuting, trade and spillovers in their exact hat form. The remaining equations are either trivially converted into this form (e.g. (14))) or are used in their levels form (e.g. (20)).

For dynamic transitions, the equations are identical to those in CDP, except that flow utility is differently specified, due to the inclusion of commuting:

$$\mu_{t+1}^{kr,lq} = \frac{\mu_t^{kr,lq} \left(\dot{V}_{t+2}^{lq} \right)^{\beta/\nu}}{\sum_{l'=1}^{J} \sum_{q'=1}^{N} \mu_t^{kr,l'q'} \left(\dot{V}_{t+2}^{l'q'} \right)^{\beta/\nu}}, \tag{29}$$

and

$$\dot{V}_{t+1}^{kr} = \dot{U}_{t+1}^{kr} \left(\sum_{l=1}^{J} \sum_{q=1}^{N} \mu_t^{kr,lq} \left(\dot{V}_{t+2}^{lq} \right)^{\beta/\nu} \right)^{\nu} \tag{30}$$

where, for any variable, $\dot{X}_{t+1} \equiv X_{t+1}/X_t$.

For commuting, the change in expected residence utility is

$$\dot{U}_{t+1}^{kr} = \left(\sum_s \left(\psi_t^{krs} \frac{\dot{m}_t^{krs}}{\dot{P}_t^r \dot{D}_t^{rs}} \right)^{\epsilon_k} \right)^{1/\epsilon_k}. \tag{31}$$

and in workplace shares is

$$\psi_{t+1}^{krs} = \left(\frac{\dot{m}_{t+1}^{krs}}{\dot{U}_{t+1}^{kr} \dot{P}_{t+1}^r \dot{D}_{t+1}^{rs}} \right)^{\epsilon_k} \psi_t^{krs} \tag{32}$$

For trade, the equations are identical to those in CDP. However, I do not observe trade flows between small sub-national spatial units, therefore base year flows are constructed using model equations in levels with estimates of trade frictions based on transport costs and parameters from the literature. Initial trade source shares π_0^{irs} can then be updated as follows:

$$\pi_{t+1}^{irs} = \pi_t^{irs} \left(\frac{\dot{p}_t^{ir} \dot{t}_t^{irs}}{\dot{P}_{t+1}^{is} \left(\dot{A}_t^{ir} \right)^{\alpha_V^i}} \right)^{-\theta^i}, \tag{33}$$

and

$$\dot{P}_{t+1}^{is} = \left(\sum_{r=1}^{N+1} \pi_t^{irs} \left(\frac{\dot{p}_t^{ir} \dot{t}_t^{irs}}{\left(\dot{A}_t^{ir} \right)^{\alpha_V^i}} \right)^{-\theta^i} \right)^{-1/\theta^i} \tag{34}$$

Spillovers can be thought of as the result of flows of information, knowledge, and know-how. Again, these are unobserved, so I construct the base year flows using model equations in levels, transport costs and parameters from the literature. Initial source shares for the effective density experienced in a location are given by

$$\vartheta_0^{rs} = \frac{\exp\left(-\varrho g_0^{rs}\right) L_0^{ks}}{\sum_{q=1}^{N} \sum_{k=1}^{O_H} \exp\left(-\varrho g_0^{rq}\right) L_0^{kq}}. \tag{35}$$

These shares and the associated spillover effects can be updated as follows:

$$\vartheta_{t+1}^{rs} = \vartheta_t^{rs} \frac{\exp\left(\varrho\left(g_t^{rs} - g_{t+1}^{rs}\right)\right)}{\dot{\Theta}_{t+1}^r} \frac{\sum_{k=1}^{O_H} L_{t+1}^{ks}}{\sum_{k=1}^{O_H} L_t^{ks}}, \tag{36}$$

and

$$\dot{\Theta}_{t+1}^r = \sum_{s=1}^{N} \vartheta_t^{rs} \exp\left(\varrho\left(g_t^{rs} - g_{t+1}^{rs}\right)\right) \frac{\sum_{k=1}^{O_H} L_{t+1}^{ks}}{\sum_{k=1}^{O_H} L_t^{ks}}. \tag{37}$$

Changes in productivity are then given by

$$\dot{A}_t^{ir} = \left(\dot{\Theta}_{t+1}^r\right)^{\chi_i}. \tag{38}$$

3. Bringing the model to the data

3.1. Economic database

A model master database is constructed at the level of Australian Statistical Geography Standard (ASGS) 2016, Statistical Area 2 (SA2) (Australian Bureau of Statistics, 2016b), sub-major occupational groups from the Australian and New Zealand Standard Classification of Occupations (ANZSCO) and Australia New Zealand Standard Industry Classification (ANZSIC) Divisions. The database consists primarily of: (i) a transition matrix for residential locations and occupations; (ii) a matrix of commuting flows for each occupation; (iii) a matrix of local occupational labour demands for each industry; (iv) a matrix of local occupational wage rates; and (v) a matrix of trade flows for each good or service. Additionally, production technologies, consumer preferences and tax rates are identified from national input–output tables (Australian Bureau of Statistics, 2019).

The first three sets of matrices are derived directly from Census count data (Australian Bureau of Statistics, 2016c). For the latter two, it is only necessary to reconcile different cross-tabulations. For this purpose, I use a bi-proportional scaling procedure. Counts are subject to error (e.g. persons providing no or incomplete responses) and small counts are perturbed for reasons of confidentiality. Thus, I sequentially impose control totals at national, state and large region (SA4) levels, and totals over occupations and over industries.

For the transition matrix, data limitations are more significant. The full matrix would have around nine billion entries. There are around 11.5 million persons in the Australian labour force, thus the vast majority of entries in such a matrix are zero. My solution is to first impute a matrix of transitions for occupations and (the much larger) SA4 residence regions. Then, to support any particular model implementation (i.e. given some significant aggregation of spatial units and/or occupations) I spatially downscale this matrix as required.[8]

Even at SA4 level, the full matrix of transitions is unavailable in the Census. I impute it from (i) an array of SA4 level migrations by 2016 occupation and (ii) matrices of occupational transitions at the national level, distinguishing workers who have the same residential address in 2011 and 2016 from those who do not. The matrices are derived from census longitudinal data (Australian Bureau of Statistics,

[7] Note that the ratios described here are in fact 'dot' variables in CDP. Their 'hat' variables are ratios of these dot variables in the policy versus the base case. This second stage yields further theoretical insights but is not important to the numerical solution of the model.

[8] More specifically, for each occupation-by-SA4(2011)-by-SA4(2016) cell, I use the all-occupations pattern of migration between SA2s (2011–16) to perform a preliminary spatial disaggregation of the SA4 level transition matrix entries. I then apply bi-proportional scaling to adjust these priors to match previously constructed row and column totals. These totals give resident worker population by occupation for the chosen spatial units in 2011 and in 2016 respectively. Finally, occupations are directly aggregated if required.

2016a).[9] Finally, the transition matrix must match the simulation time period. In the simulations below, I use 2.5-year periods, so halve the off-diagonal 5-year flows and add these differences to the diagonal.

Wage rates are estimated for sub-major occupations by SA2 from the survey-based Employee Earnings and Hours (Australian Bureau of Statistics, 2016d) combined with Census data on employment by place of work and individual income. The Census only provides counts by broad income bands, so I estimate average wages using the mid-points of each band. I adjust the raw averages in each location for within-occupation heterogeneity by using counts of 4-digit occupational employment within each 2-digit group and the national average wage rates for 4-digit occupations.

The trade matrix is largely unobservable as relevant statistics are very limited. I impute trade flows to balance the supply of and demand for goods or services in each location using Eq. (19). For this purpose, I need the iceberg trade costs in levels. The estimation of relevant transport costs and their conversion to iceberg trade costs is covered in the next two sections. I extend the procedure to international imports and exports following the approach in CDP.

3.2. Behavioural parameters

Many model parameters are calibrated directly from the underlying data. For example, exponents in the production function match value shares. Tax rates are similarly observed. However, a number of parameters remain for which values must be estimated or assumed. Given data limitations in Australia at smaller spatial scales, I am able to estimate only the parameters relating to commuting. Values for the remaining parameters are taken from the literature.

The model requires changes in (but not the original levels of) the disutility of commuting to be specified. As in Ahlfeldt et al. (2015) I assume a negative exponential form: $D_t^{rs} \equiv \exp\left(-\kappa\, t_t^{rs}\right)$ where t_t^{rs} is a generalised composite cost that may be considered to have units of minutes. While these factors apply to all workers, ϵ_k is specific to each occupational group. This is analogous to the treatment of skilled and unskilled workers in Warnes (2022). For the application reported in this paper, I aggregate the occupations into three 'collar' groups that have particular relevance to commuting behaviour: blue, pink and white. I run Poisson regressions to estimate commuting semi-elasticities, and divide these by κ, obtain estimates of $\epsilon_k = 4.2$, 4.3 and 4.0 for workers in blue-, pink- and white-collar occupations respectively. These values are within the range typically reported in the literature. They are slightly above the recently estimated $3.6 - 3.9$ for Australian capital cities in Donovan et al. (2021). These regressions are reported in Appendix A, along with a concordance between 1-digit ANZSCO groups and the three collar groups.

I assume that the elasticity of all trade flows with respect to transport time is 1.25, around the middle of the range reported in Caliendo et al. (2018, tb A7.1).[10] This value is the product of the elasticity of the iceberg cost factors to transport time and the price elasticity θ_i. For the latter, I assume a typical value of $\theta_i = 5$ for all sectors (e.g. Caliendo et al., 2018, tb A4.1).[11] I therefore set the iceberg cost elasticity equal to 0.25 for all sectors. I adopt a 2.5-yr discount factor of $\beta = 0.9$, equivalent to an annual discount rate of approximately 4%. Given that it is a key parameter, it would be desirable to estimate the inverse migration elasticity ν, but I have insufficient data. I therefore choose a value based on the literature—which it should be noted, is still in its infancy. Most estimates pertain to migration between US states or countries. However, Warnes estimates values of 1.4 and 1.8 for high- and low-skill workers respectively within the city of Buenos Aires. Estimates for migration between EU countries (Caliendo et al., 2021) or US states (CDP) are closer to $\nu = 2.0$. These estimates are based on annual data. The effective elasticity for a longer period will be higher.[12] Here, I adopt a 2.5-year simulation time-step and intra-urban migration dominates inter-urban/inter-regional movements. Consequently, I choose a lower value of $\nu = 0.75$.

To model productivity spillovers, I assume $\chi_i = 0.07$ for all industries and $\varrho = 0.33$ (Ahlfeldt et al., 2015). I assume there are no such spillovers in the provision of housing services.

3.3. Transport costs

Transport costs are needed for two reasons. This section describes the estimation of travel times for the purpose of estimating trade flows in the master database. For this purpose, I consider only road and air travel. In Section 4.3, I explain how the method is extended to consider urban public transport.

I estimate point-to-point road travel times from OpenStreetMap (OSM) (OpenStreetMap contributors, 2017) and efficient shortest path algorithms (Dibbelt et al., 2016). Where relevant, vehicle ferry links (e.g. to North Stradbroke Island, Queensland) are included in the road network. Road speeds are estimated using a regression relationship identified between observed speeds in NSW and the ACT (Transport for New South Wales, 2017), the corresponding posted speed limits from OSM, and a custom measure of betweenness centrality[13], which I compute for every link of the national road network.

For trade in goods, I use these road travel times and add a fixed time penalty of 60 min to account for loading, unloading, etc. For trade in services—I assume that business-to-business trade is associated with business travel and consumer services with private travel.

In quantifying transport costs between SA2s, it is important to consider that these often have irregular geometries. Moreover, in peri-urban and rural areas, SA2s can be very large. I use the following procedure:

1. Select a road network node at random to represent each Mesh Block in each SA2. A Mesh Block is the smallest spatial unit in the ASGS, comparable to a US census tract.
2. Estimate travel times between all pairs of such nodes.
3. For each pair of SA2s, combine all estimates corresponding to trips between these regions using a log-sum aggregator.

A benefit of the algorithm is that it also produces comparable estimates for intra-SA2 travel times (omitting trips beginning and ending in the same Mesh Block in this case).

To allow for long business or private trips, I adjust the SA2-level matrix of road travel times so that flights are used if this makes a trip shorter. Gate-to-gate air travel times between all major and regional airports are compiled manually from results obtained querying the commercial flight planning service (webjet.com.au). I add 60 min to trips involving flights to account for airport access, waiting and egress.

[9] I use the same address flag to proxy for transitions without a change in SA4 of residence.

[10] Note that most available estimates are limited to traded goods because they rely on international statistics on bilateral trade flows, which are very limited for flows of services. Distance is more often used than time as a dependent variable, but the two are strongly correlated.

[11] Note that literature estimates of these parameters rely on international (or in some cases US interstate) trade statistics.

[12] The opposite holds for shorter periods. A value over 5 is estimated using quarterly data in CDP.

[13] Betweenness centrality measures the importance of a link by counting the number of shortest paths that use it. My measure considers paths from 4–60 min travel time and weights each path by the factor $e^{-0.07t}$, where t is the path length in minutes. These path times are based on the posted speed limits.

4. Simulations

4.1. Solution algorithm

The solution algorithm is based on the nested fixed point algorithm described in CDP. The main modifications to that algorithm are as follows:

- Having occupational rather than industry-specific labour, I iterate on a vector of local occupational wage rates and land prices.
- Labour supply is computed by applying commuting probabilities to the resident workforce. Commuting probabilities are also used when computing average occupational wage rates (and thus income) by place of residence. These commuting probabilities are updated in the outer loop used to solve each period equilibrium, applying a continuation factor of 0.5 to achieve stability.
- As the trade/input–output matrix is very large, it is more efficient to account for intermediate demands using another nest of fixed point iterations than using matrix inversion. These iterations are initialised with the solution from the previous time period.
- In both the outer period equilibrium loop (i.e. iteration on changes in factor prices) and the outer-most loop (i.e. iteration on changes in utilities) I find an alternate secant acceleration method (Ramière and Helfer, 2015) provides faster and more reliable convergence than using fixed weights.

I implement the model and solution algorithm in C++, making extensive use of the Eigen template library for linear algebra (Guennebaud and Jacob, 2010). To read and write data in Numpy npz file format, I use the C++ cnpy library (Rogers, 2018). Figures and tables below are produced using Matplotlib (Hunter, 2007) in Python and QGIS (QGIS Development Team, 2021).

Forward-looking models with multiple forms of spatial interactions may have persistent or even path-dependent dynamics and admit multiple solutions (Allen and Donaldson, 2020). However, the many recent applications of such models in the literature suggest that such complications are rare given realistic shocks and typically estimated parameter values. KLR show that in a somewhat similar DSM, a unique solution exists if spatial externalities are not 'too strong'.

I do not offer a theoretical proof of the existence or uniqueness of the model's solutions here. However, computational experience with the present model shows, firstly, that in simulations, forward-looking variables reliably converge to a solution as the number of outer iterations is increased. There is negligible difference in the solution if either the primary inner loop tolerance or the continuation factor are reduced. Secondly, in counter-factual simulations of temporary shocks (e.g. to transport costs), variables return over time to their baseline values. This provides confidence that, in practice, the model's solutions are unique and not path-dependent.[14]

4.2. Baseline

The baseline economy is defined in the simplest possible way. The database is constructed with a base year of 2016. I fix aggregate population. However, the initially observed transitions are inconsistent with a steady state. Thus, in the baseline simulation, the economy evolves gradually from its initial condition until steady-state levels are reached. Through this adjustment, I hold the trade balance fixed and allow the exchange to vary.

A DSM is not intended as a forecasting model, thus this baseline should not be treated as a forecast. Nevertheless, we can gain some insight into the ability of the model to represent key aspects of underlying data-generating processes by comparing changes in endogenous model variables with corresponding observations.[15] In the spirit of the exercise conducted by Balboni (2021), I compare local growth rates in baseline variables from 2016 to 2021 to corresponding rates computed from 2016 and 2021 census data.

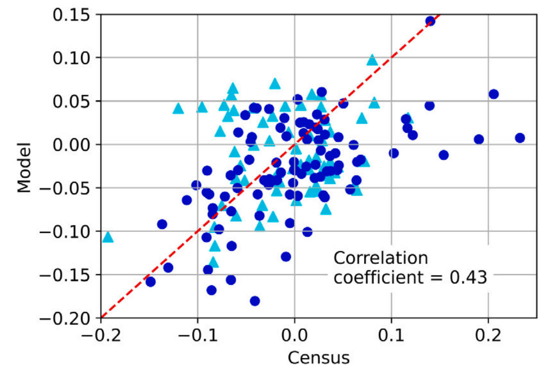

Fig. 1. Resident workforce growth 2016–21 in model baseline vs census data for Queensland SA3s. Notes: Blue circles for SA3s and cyan triangles for SA4s. Dashed red 45°line.

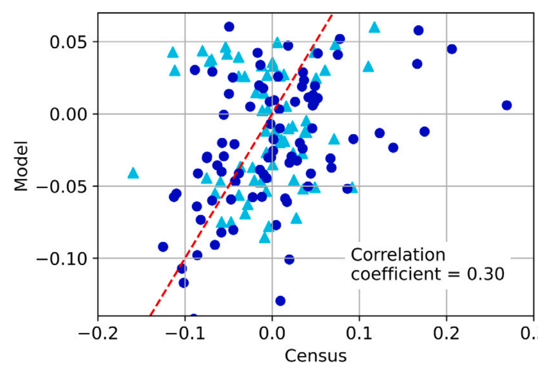

Fig. 2. Jobs growth 2016–21 in model baseline vs census data for Queensland SA3s. Notes: Notes: Blue circles for SA3s and cyan triangles for SA4s. Dashed red 45°line.

Since the model allows for commuting, I compare growth rates for both resident workers and jobs. I perform these comparisons at SA3 where the model represents SA2s or SA3s and at SA4 level for the rest of Australia. For consistency with the modelling assumptions, I scale census data to hold the national labour force at its 2016 size. As shown in Figs. 1 and 2 for resident workers and jobs respectively, the model does a reasonable job of explaining observed growth rates with correlation coefficients of 0.43 and 0.30 respectively. There are some outliers, but most of the points in each plot are clustered around the 45°line. That is despite the significant effects of the COVID-19 pandemic on international and internal migration and employment.[16]

4.3. Simulating an urban transport project

To illustrate the application of the DSM to an urban transport project, I consider introduction of a hypothetical 'fast express' service on SEQ's Gold Coast Line.[17] My hypothetical service travels between Helensvale (Gold Coast) and Central (Brisbane) via Beenleigh, Dutton

[14] Results of these simulations are available on request.

[15] I thank an anonymous reviewer for making detailed comments and suggestions on this point.

[16] Australia's international borders were closed to nearly all international tourists, international students (who often work part-time) and working holiday-makers from Q2 2020 until Q1 2022. There were also repeated closures of state borders to non-essential travellers and impositions of local travel restrictions.

[17] Note that an actual upgrade of this line is underway, but has the primary aim of doubling passenger capacities between Brisbane and Beenleigh and the

Park and Roma St stations. This entire trip takes 28 min. This is over twice as fast as the 'express' service on the current network, which takes 65 min and serves nine intermediate stations.

The method of estimating travel times described in Section 3.3 does not include trips using train and/or bus services. Thus, to characterise the benefits of the fast express service, the method must be extended. To do this, I construct a three-layer network of the SEQ region. Trip origin and destination nodes are located in the outer layers, which are OSM-derived pedestrian networks. Initial public transport (PT) access and egress nodes are also located in these layers. The intermediate layer describes the transit network. Links in this layer correspond to train, bus or transfer legs. The latter may include walks of up to ten minutes. For example, one might: (i) walk from home to a bus stop; (ii) after waiting for a bus, catch it to a rail station; (iii) after waiting for a train, catch it into the CBD; and (iv) walk from the CBD station to one's office. The second and third of these steps are routed through the middle network layer.

As in Section 3.3, costs between SA2 origin–destination pairs are log-sum composites computed over many possible trips between particular nodes. However, the latter are now stylised log-sum composites of the generalised costs for car and walk-access-PT modes.[18] Composite travel times are computed as

$$t^{krs} = \ln\left[0.8\exp\left(0.083\, t_{c,t}^{\mathrm{Car},rs}\right) + 0.2\exp\left(0.083\, t_{c,t}^{\mathrm{PT},rs}\right)\right], \tag{39}$$

where c indicates the base or project case respectively. The coefficients on modal travel times are from the all-occupations estimate of $\epsilon\kappa$ (see A.3). These times are used to compute changes in the disutility of commuting and in the iceberg transport costs for retail and services sectors, as described in Section 3.3.

This methodology cannot account for effects on transport network congestion. Doing so would require access to a fully-fledged transport model. This limitation motives my choice of a relatively simple and modest project—improvement of an existing radial rail line. Plausibly, direct travel time savings in this project would dominate congestion effects. Moreover, to the extent that substitution of car trips for rail trips reduced congestion along parallel radial road routes,[19] the true effects on composite travel costs should not be qualitatively much different to the estimates used here.

I assume construction works take place over the first three 2.5-year periods of the simulation, while the operational phase commences in the fourth period, i.e. from 2026. Aggregate construction costs of A\$960 m are allocated equally across eight SA2s around stations and ramp up over time, doubling each year. Operating and maintenance (O&M) costs are assumed at A\$30 m p.a., half of which I allocate to a major rail depot at Bowen Hills.

For simplicity, I assume that both transport benefits and O&M costs continue in perpetuity. Construction is financed by borrowing on international markets, with each tranche of borrowing repaid as a perpetuity. As noted above, the trade balance is held constant at its initial value in the baseline simulation. In the project case simulation, in each year, new borrowings for the project are deducted from and repayments are added to the baseline trade balance. This smooths out aggregate consumption over time in a plausible manner.

A project of this sort would probably be funded primarily by the Queensland government, possibly with some contribution from the Commonwealth. However, state governments depend heavily on fiscal

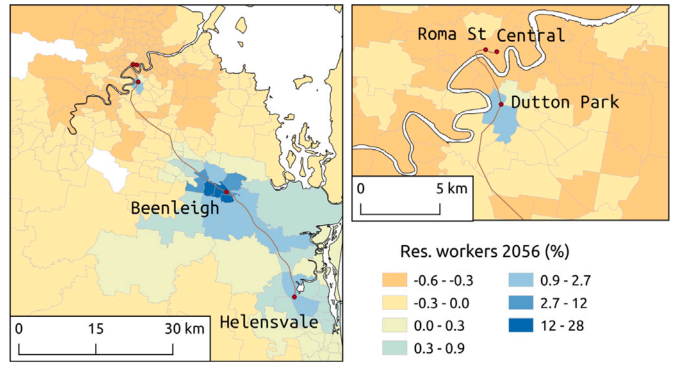

Fig. 3. Percent changes in resident workers in the project case versus the base case in 2056. Notes: The figure shows increased residential densities around suburban stations due to the project, with the greatest differences around Beenleigh station.

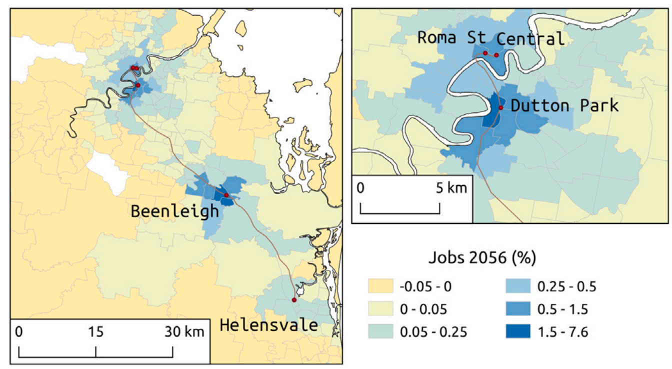

Fig. 4. Percent changes in jobs in the project case versus the base case in 2056. Notes: The figure shows increased job densities in Brisbane city centre. There are also increases around suburban stations, but they are much smaller than the corresponding increases in residential densities.

transfers from the Commonwealth and on land and property taxes. For these reasons, I assume that funding will ultimately rely on land taxation. These taxes are non-distortionary but have distributional implications. The latter cannot be assessed using the model itself (see Section 2.5), but making simplifying assumptions regarding land ownership, I am able to provide an analysis of implications at the regional scale.

5. Results

5.1. Land use changes

Fig. 3 shows changes in the resident workforce in 2056 while Fig. 4 shows changes in jobs. I choose this year to illustrate the long-run spatial impacts of the project because it allows enough time for most of the impacts to play out, as will be seen below.

Relatively large population gains are concentrated in three SA2s around Beenleigh station. Population gains around Helensvale station at the southern end of the line and in Dutton Park in Brisbane's inner south are modest. Small gains are diffused widely in the southern half of the corridor, including SA2s in which the effects of the project on accessibility are minimal. The largest relative job gains are also seen around Beenleigh station, but these are about one-quarter the size of the residential gains. In Dutton Park, there are gains of approximately 1.4% in both residents and jobs. Finally, there are modest job gains around the CBD stations, whereas here, the residential population falls slightly. Overall, the new service tends to strengthen an existing pattern of in-commuting to the city centre from the outer south-eastern suburbs.

Movements of residents and jobs seen above (Figs. 3 and 4) occur slowly. Fig. 5 shows percentage changes in resident workers and jobs.

Gold Coast. See https://www.tmr.qld.gov.au/projects/logan-and-gold-coast-faster-rail, accessed 29 March 2022.

[18] Many users of Helensvale and Beenleigh stations actually access these stations by car. One could model this as a third mode : 'park-and-ride'. However, the simplified transport modelling approach adopted is sufficient for the purposes of this paper.

[19] One can drive from Helensvale to Brisbane CBD using the M1 freeway to Springwood, then the M3.

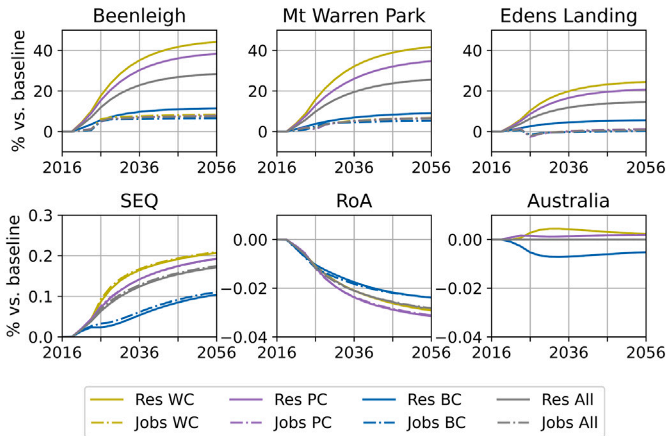

Fig. 5. Changes in resident workers and jobs around Beenleigh station (upper plots), for the SEQ and RoA regions, and nationally (lower plots). Notes: 'Res' = by place of residence, 'Jobs' = by place of work, WC = white collar, PC = pink collar, BC = blue collar. Increases in residential densities around Beenleigh station (upper plots) unfold over several decades but begin even before the operational phase of the project commences. At a regional scale, population gains in SEQ unfold even more slowly and favour white- and to a lesser extent, pink-collar workers over blue-collar workers (lower left). As we hold the national population fixed, regional population gains are offset by population losses from RoA (lower centre). However, there is a shift at the aggregate level away from blue-collar occupations and towards pink- and white-collar occupations (lower right).

These are shown by occupational collar (WC = white collar, PC = pink collar, BC = blue collar) and overall in three SA2s around Beenleigh station (top panel), and for the whole of SEQ, the rest of Australia (RoA, i.e. the remainder of Queensland plus all other states and territories) and Australia (bottom panel). Note that while the total Australian workforce is exogenous in the simulation, the numbers of workers in each occupation are endogenous.

Recalling Fig. 3, the three SA2s around Beenleigh are those with the largest population gains. These gains begin before the project's operational phase in 2026 and are largely played out by 2056. Population gains in white-collar and, to a lesser extent, pink-collar occupations are much larger than those for blue-collar occupations. This is consistent with the relatively limited work commuting opportunities the service offers to blue-collar workers. Whereas white-collar jobs are highly concentrated in inner Brisbane, blue-collar jobs are most concentrated in various industrial areas. Many blue-collar jobs are also widely distributed or mobile (e.g. drivers).

Regional dynamics play out more slowly. The SEQ region gains population at the expense of the rest of Australia. As in Beenleigh, regional gains in white and pink-collar workers are larger than those of blue-collar workers. These changes are largely mirrored in the rest of Australia. The much smaller percentage changes reflect the much larger population. Nationally, the modelled population/workforce is fixed. However, the total number of workers in each occupation is determined endogenously. The project results in a slight shift away from blue-collar occupations and towards white- and pink-collar occupations.

Anticipatory moves reflect the underlying theory of migration. Moving costs are substantial, so households tend to move infrequently. Idiosyncratic factors (i.e. factors not explicitly modelled) are a major driver of moving decisions. Thus, for example, a household determined to relocate for one reason or another in 2021 will consider their expected *future* utility in various possible destinations, including the local benefits of the project that are realised from 2026 onwards. By comparison, the construction phase has only modest effects on location choices, not least because it lasts only three model periods (7.5 years). The effects are most important for blue-collar workers in SEQ. There is a slight kink in the trajectories of blue-collar residents and jobs moving from the construction to the operational phase.

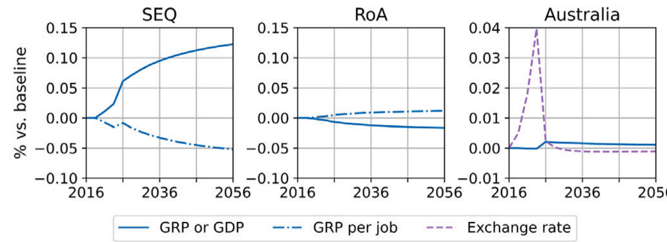

Fig. 6. Changes in real GRP or GDP (blue solid lines), GRP per job (blue dash-dotted) or nominal exchange rate (orange dotted). Notes: As GRP per capita falls in SEQ as population rises (left) and rises in RoA as population falls (centre), congestion effects dominate agglomeration effects. At the national scale, there is a clear step gain in productivity as the project comes on line. The initial spike and then permanent decline of the exchange rate reflect the changes imposed on the balance of trade to represent project financing.

5.2. Economic impacts

Fig. 6 shows changes in real gross regional product (GRP) and GRP per job in the SEQ and RoA regions. For Australia, changes in gross domestic product (GDP) and the real exchange rate are shown. GDP and GDP per capita are equivalent in this case because I hold the total number of workers constant. Note that GRP per job has a straightforward interpretation as a measure of (single factor) labour productivity, whereas GRP per resident is not easily interpreted in regions open to commuting.

GRP for the SEQ region increases as the project attracts more workers and jobs, especially after 2026. However, notwithstanding some positive effects of agglomeration on productivity, the larger workforce has the overall effect of reducing output per worker because land becomes relatively scarcer. The opposite effects are seen in the rest of Australia. The slight jump in labour productivity in 2026 reflects the direct productivity benefits of the project due to agglomeration and improved accessibility to higher-valued white and pink-collar jobs in inner Brisbane.

Productivity gains are most clearly seen at the national scale, where movements of resident workers and jobs cancel out. There is a step increase in GDP from 2026. Movements in the real exchange rate reflect the schedule of foreign borrowing and repayments that finance the project. Borrowing is associated with a fall in the balance of trade, enabled by a real appreciation. Repayments are modelled as a perpetuity, so require a permanent (albeit slight) real depreciation.

5.3. Welfare impacts

With dynamic adjustment costs, impacts on welfare depend on one's initial location and occupation. Fig. 7 shows welfare gains by initial residence and occupation. The largest gains are seen in SA2s around Beenleigh station (top panels). The grey bars are person-weighted averages. The bottom panels show weighted-average welfare impacts for SEQ, the rest of Australia, and Australia as a whole.

For white-collar workers living closest to the station, gains are equivalent to a permanent 1.5% increase in consumption. Note that these results are exclusive of any capital gains that might be derived from the appreciation of local property, a point which I consider in Section 5.4. Gains are slightly smaller for pink-collar workers than for white-collar, and approximately half the size for blue-collar workers. This pattern is consistent with the different distributions of employment in these occupational groupings (see Section 5.1).

Considering the SEQ region as a whole, gains are relatively smaller. Less obviously, the ordering is reversed: blue-collar workers benefit most and white-collar workers least. Whereas direct accessibility benefits are more important in areas closest to stations, general equilibrium

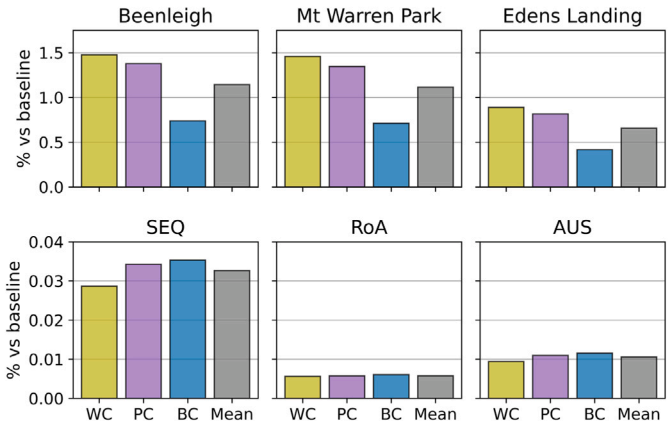

Fig. 7. Welfare effects around Beenleigh station (upper plots) and at regional and national scale (lower plots). Notes: WC = white collar, PC = pink collar, BC = blue collar. Initial headcounts are used in weighted averages over occupations and/or spatial units. The much larger gains around Beenleigh station point to the importance of relocation costs in concentrating benefits amongst the original residents. Nevertheless, there are net gains in almost all locations, even outside of SEQ.

effects in housing, labour and product markets dominate elsewhere.[20] The modelled benefits also account for the gains experienced by those who later move into locations seeing direct accessibility benefits.

Similar reasoning applies to the results for the rest of Australia, except that these results include no direct accessibility benefits. Benefits result from migration, commuting and trade linkages between the RoA and SEQ regions. Recall that I assume the project is funded by the taxation of land in SEQ (Section 4.3). However, in the model, aggregate net income from land is distributed to all households pro-rata with labour income. Consequently, the results presented in this section reflect the same pro-rata distribution of project funding costs. In Section 5.4, I indicate how regional average welfare results are affected by *ex-post* adjustments to reallocate funding costs to those initially resident in SEQ.

Local and regional impacts are important when considering the project's impacts on regional economic development or equity. However, in selecting projects, a crucial concern is whether the overall ratio of benefits to costs is sufficient to justify devoting limited resources to one project over other potential projects. The national average 0.0077% consumption-equivalent welfare gain corresponds to \$41.9 m p.a. of net benefits (i.e. accounting for funding costs). Funding costs alone are equivalent to a permanent consumption loss of \$34.8 m p.a. Thus, the modelled project's national benefit-cost ratio is $1 + 41.9/34.8 \simeq 2.2$. Notably, almost half (44%) of the net benefits accrue to persons initially incumbent outside of the SEQ region. However, the regional distribution of benefits is sensitive to particular modelling assumptions, as I show next.

5.4. Capital gains and project funding

As explained in Section 2.5, national land rents are distributed pro-rata with labour income in the model for practical reasons. In reality, asset holdings have substantial regional and local home biases. Most importantly, a majority of Australian households are home owner-occupiers. Ownership of rental housing and non-residential property is likely to be regionally biased. To indicate the scope for such biases to alter regional welfare results, I present here the results of off-model adjustments that 'reallocate' capital gains/losses as if all SEQ/non-SEQ property was owned by regional residents. In this case, SEQ owners bear the entire project funding costs.

[20] Recall that I have not modelled indirect impacts on the transport here, but these might also play a significant role.

Table 1
Annual consumption-equivalent welfare impacts of the project as modelled, and adjustments reflecting alternative assumptions on the regional incidence of capital gains and project funding.

	SEQ	RoA
Originally modelled (\$m p.a.)	23.5	18.5
Originally modelled (% change)	0.030	0.0039
Adjustment for capital gains (% change)	0.015	−0.0025
Adjustment for regional funding (% change)	−0.039	0.0065
Adjusted net benefits (% change)	0.004	0.0079

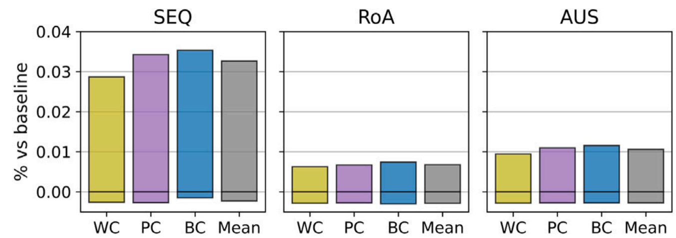

Fig. 8. Decomposition of welfare effects into effects of operations (positive bars) and of construction and O&M (negative bars). Notes: WC = white collar, PC = pink collar, BC = blue collar. The positive bars reflect the results of a simulation in which only changes in transport costs are modelled. The negative bars represent the results of a simulation in which only the construction, financing and funding aspects are modelled.

I first compute capital gains (losses) as the present value of modelled changes in land rents in the project case, relative to the base case.[21] I then compute the present value of project finance. These values are converted to per-period values by multiplying by 0.1 for comparability with consumption-equivalent welfare measures. Finally, I divide these by initial consumption. Note that I subtract originally modelled national average values before adding region-specific values. Table 1 shows how the regional average welfare values change with these adjustments.

If SEQ captures 100% of regional capital gains, the increase in average welfare is 50% larger than that modelled. The benefits to those outside of SEQ are reduced by 64%. However, the adjustments associated with raising project funds from SEQ residents alone are larger still. In this case, the average net benefits in SEQ are lower in SEQ than in the rest of Australia. With some cross-regional ownership and a funding base likely to extend beyond SEQ (e.g. due to the use of statewide land taxes or federal government contributions), the results would lie between these extremes.

5.5. Contributions of construction and operational components

One way to obtain further insight into the model results is to individually simulate project components. Fig. 8 shows regional welfare results in simulations with only: (i) changes in travel costs; and (ii) only construction and operational expenditures, financing and funding. As already explained, the modelling assumptions mean the direct funding costs are shared more-or-less equally by all workers. However, the construction activities enabled by the financing and funding are concentrated along the rail corridor. Thus, labour demand, particularly for blue-collar workers, increases in SEQ during the construction phase. This explains the smaller welfare losses for SEQ blue-collar workers in the second simulation.

[21] Noting that 'land' rents here include gross capital rents, I discount this component of the rents at a higher rate to allow for depreciation of 10% per 2.5-year period.

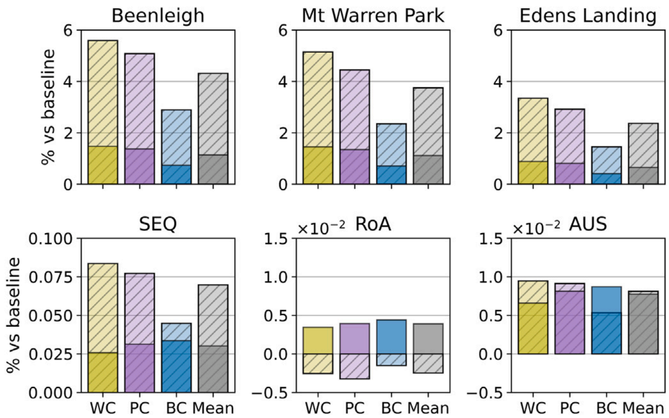

Fig. 9. Effects of eliminating residential and occupational mobility on welfare. Notes: light hashed fill = SSSE, dark plain fill = DSM, WC = white collar, PC = pink collar, BC = blue collar. Steady-state spatial equilibria (SSSE) simulations 'switch off' the dynamic residential and occupational choices present in the full model simulation (DSM). Residential location and occupational choices are important to diffusing welfare benefits spatially but do not greatly affect their aggregate scale.

5.6. The role of migration

Fig. 9 shows the effects of 'switching off' the dynamic location and occupational choices in the model. I achieve this by simulating a series of steady-state spatial equilibria (SSSE) in which residents' 2016 locations and occupations are fixed for all time. Residents can still endogenously switch job locations in response to changing commuting costs and wage rates.

Welfare gains around Beenleigh station would be two to three times larger if it were not for residential and occupational mobility. The incumbent resident workers would reap the accessibility gains delivered by the project but would not suffer the upward pressure on living costs and downward pressure on wages caused by the influx of additional resident workers. Welfare gains in SEQ as a whole are also larger in the SSSE simulation than in the DSM simulation. However, for the RoA region, this pattern is reversed—and in fact, gains in the DSM simulation become losses in the SSSE simulation.

These results show that residential and occupational mobility are critical to the spatial diffusion of welfare benefits. However, they make little difference to the aggregate scale of benefits. In the bottom-right plot, the mean welfare changes are nearly identical: 0.0081% in the SSSE versus 0.0077% in the DSM. It is important to note that this result obtains with exogenous changes in transport costs. The effects of residential and job relocations on transport network congestion are not considered here. A complete analysis must account for the effects of land use change on transport costs, i.e. for bi-directional land use–transport interactions.

6. Discussion

6.1. Costs and benefits of projects in dynamic spatial equilibrium

With discounting, the dynamics of adjustment affect the time paths of direct and indirect costs and benefits, their present values and thus, the overall cost–benefit ratio. Migration and other adjustment costs also affect the distribution of benefits and costs. At one extreme, if migration costs are very high, a project has little potential to induce land use changes, and most benefits will be captured by incumbents. At the other extreme, the land use change response will be stronger and faster with very low migration costs, and a high proportion of benefits will be capitalised in local property values. Our simulation represents an intermediate case in which significant land use changes unfold over decades. Together with commuting and trade linkages, relocations of residents play a major role in the spatial diffusion of the simulated project's benefits throughout and beyond SEQ.

A limitation of the model is that it does not realistically account for the distribution of project-related capital gains or losses. Not only is it impractical to model the asset holdings of spatially mobile agents with many regions, but relevant data are not publicly available (a notable exception is available census data on own home ownership). This limitation does not affect estimates of the costs and benefits of a project on a national scale, except insofar as affected assets are foreign-owned. However, I show with some simple *ex-post* calculations that home-region bias—and the interaction of funding instruments with this—could significantly alter the share of net benefits captured by incumbent residents of South East Queensland versus those in the rest of Australia.

From a policy perspective, the results highlight the significance of assumptions often explicitly or implicitly made in economic appraisals of urban transport projects. The spatial extent of models used is often limited to a metropolitan region or a single state. This neglects wider economic interactions, including migration. Indeed, a fixed regional population is usually an explicit modelling assumption, even in studies that account for local land use changes. On the other hand, project financing and funding are often modelled only as discounted cash flows without regard to general equilibrium effects or economic incidence. Our simulation results are consistent with a view that such simplifications should not significantly affect the overall cost–benefit ratio of a project. However, they may substantially affect the distribution of costs and benefits both within and outside a large metropolitan region.

With multiple occupations and industries, the DSM model captures heterogeneity that may be relevant to the distribution and overall magnitude of a project's costs and benefits. In the simulation, the improved accessibility to the CBD delivered by a fast express rail service has more benefit to white- and pink- than to blue-collar workers. However, blue-collar workers benefit more from increased labour demand in the construction phase. I obtain this result even while assuming full aggregate employment, but it would be useful to extend this framework to allow for effects on labour supply and/or involuntary unemployment. Construction-related effects should not be a dominant factor, but they do often attract particular policy attention: politicians are eager to claim that large projects are 'creating jobs'. Finally, dynamic occupational switches provide a further channel for the diffusion of benefits in the model. From a national perspective, such a project is likely to have productivity benefits if it delivers a net increase in agglomeration of employment and/or increases labour supply to more productive jobs.

For simplicity, I omit two potentially important dynamic factors from the present model. Firstly, I treat land and capital combined as a fixed factor. KLR show that dynamic interactions between structures and other fixed capital and migration may be significant. I intend to allow for this in future work but note that KLR's device of 'immobile capitalists' is ill-suited to the small spatial scales I consider. Secondly, developments considered at small spatial scales are prone to be 'lumpy'. For example, the model will typically show increased residential density supporting increased retail activity. However, it cannot predict when, where or if an entire new suburban shopping centre will be built. Such difficult issues are only beginning to be addressed in spatial economic models (see e.g. Ahlfeldt et al., 2022).

6.2. Implications for modelling land use/transport interactions

The simulation presented here illustrates the effects of given changes in transport costs. These inputs would usually be derived from a four-step transport model. As in Le et al. (2021), this requires producing composite generalised costs from detailed skim matrices that summarise costs by mode and other factors, e.g. travel purpose, time-of-day and day-of-the-week. It may also be necessary to spatially aggregate costs. However, the use of a DSM model in a LUTI framework poses some additional challenges.

In principle, I require transport cost changes for every origin–destination pair and purpose and every period of the DSM model simulation. However, a four-step transport model is typically developed for a major metropolitan area and represents the operation of the transport network at one point in time. In Australia, future land use patterns and networks are often defined at five-year intervals (coinciding with census years) for three to four decades. In the best case, the initial time periods of the simulation can be aligned. Alternatively, some form of interpolation scheme must be devised in a way that avoids both artefacts and convergence problems in the coupled LUTI system. Extrapolation for the later decades of the DSM simulation is also necessary but less critical. To ensure convergence of the DSM model, these changes must converge to zero in the far future. However, due to discounting, welfare results should be insensitive to these extrapolations.

By definition, a transport model can estimate changes in travel costs only within its geographic scope. If the total population of this modelled region increases, the total costs of congestion within the region should also increase, while population and congestion outside of the region should decrease. These changes may be negligibly small for any individual link in the transport network or on a per capita basis. However, in aggregate, the corresponding costs or benefits may be large. Including this effect within the region but not outside of it is liable to give misleading results. Two solutions can be envisaged. One solution is to artificially fix the regional population in the DSM model to match the transport model. This approach has limited theoretical justification but is most consistent with current transport modelling practice in Australia. A potential alternative would be to adjust external transport costs using reduced-form relationships. These could be estimated through simulations of transport models covering other major metropolitan regions.

A final question to consider is how to reconcile 'top-down' project benefit estimates from a DSM model with 'bottom-up' estimates from a transport model. Top-down estimates are more comprehensive but are based on stylised representations of transport demands and costs. Bottom-up estimates are narrower in scope but account for transport demands and costs in much more detail. One possibility may be to disentangle 'direct' from 'indirect' welfare impacts in the DSM model. Top-down estimates of indirect benefits could then be added to bottom-up estimates of direct benefits. Separately, a DSM model can be used to estimate the wider economic benefits of transport projects. That approach is taken in a comparative static setting in Le et al. (2021).

7. Conclusions

This paper presents a dynamic spatial equilibrium model featuring forward-looking decisions on internal migration and occupational choices, commuting between residence and workplace, and trade between multiple industries. Using a flexible aggregation procedure, I apply a 451-region version of the model to assess the costs and benefits of a hypothetical fast express rail service between the Gold Coast and Brisbane in South East Queensland, Australia. Not only time savings but construction and operational expenditures, funding and financing are explicitly represented in space and over time.

In the simulation, gains in accessibility drive changes in land use that play out over several decades but include a preemptive element due to households' forward-looking migration decisions. The construction phase provides a temporary boost to local demands for blue-collar workers but has little effect on land use. Intra- and inter-urban migration play crucial roles in diffusing the benefits of the project widely. Without this margin of adjustment, most benefits would be capitalised in local property values and captured by property owners. At a national scale, the benefit-cost ratio is relatively insensitive to migration responses. However, this might not be the case if the effects of land use change on transport costs were accounted for.

I discuss two key limitations of the DSM itself: inability to track ownership of fixed assets and omission of investment–capital stock dynamics. Computational difficulties and data limitations make the former very difficult to address. I intend to extend the DSM to model capital stock dynamics in future work. I also discuss the challenges involved in linking the DSM to a four-step transport model and propose some potential solutions. Such a linked system would permit comprehensive and dynamic modelling of land use—transport interactions. This would provide a sounder basis for estimating the costs and benefits of major transport projects.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dr James Lennox reports a relationship with Infrastructure Victoria that includes: funding grants. Dr James Lennox reports a relationship with New South Wales Department of Enterprise, Investment and Trade that includes: funding grants.

Data availability

The original data sources used are publicly available, but the constructed database is proprietary to Victoria University.

Appendix A. Occupational groups and commuting behaviour

Table A.2
Mapping from ANZSCO groups to 'collar' groups.

ANZSCO Major Group	Collar
Managers	White
Professionals	White
Technicians and Trades Workers	Blue
Community and Personal Service Workers	Pink
Clerical and Administrative Workers	Pink
Sales Workers	Pink
Machinery Operators and Drivers	Blue
Labourers	Blue

There are 43 2-digit ANZSCO occupations in the master database, but the three collar groups map directly to the eight 1-digit occupations. This concordance is given in Table A.2.

For each collar group k in turn, I estimate the following gravity equation

$$\ln n_{krs} = \upsilon^k t^{rs} + a^{kr} + b^{ks} + e^{krs} \tag{A.1}$$

where n_{krs} are the number of commuters of collar k living in r and working in s, the coefficient $\upsilon^k \equiv \kappa\epsilon^k$ and t^{rs} is a log-sum composite of base case travel costs:

$$t^{rs} = \frac{\ln\left[0.8\exp\left(\bar{\upsilon}t^{\mathrm{Car},rs}_{\mathrm{Base}}\right) + 0.2\exp\left(\bar{\upsilon}t^{\mathrm{PT},rs}_{\mathrm{Base}}\right)\right]}{\bar{\upsilon}} \tag{A.2}$$

I allow for fixed effects a^{kr} and b^{ks} for each place of residence and work. As I find only modest differences in υ^k by collar, I use a estimate for all collars ($\bar{\upsilon}$) in the composite cost equation for simplicity. This estimate is determined iteratively, starting with an initial guess of $\bar{\upsilon} = 0.1$. Given the very large number of zero commutes between SA2 origin–destination pairs, I follow the standard approach of using a Poisson Pseudo-Maximum Likelihood estimator.

For each regression, I drop origin or destination SA2s that have fewer than ten residents or workers respectively. The number of remaining origin–destination pairs, the percentage of these pairs with non-zero commuting flows and the associated working population are reported in the table. I obtain estimates for the commuting elasticity

Table A.3
Estimates of commuting semi-elasticities.

Collar	Estimate	Std Err	N pairs	% zeros	N pop
All	−0.0833	5.0e−5	72,900	65.3	1,109,018
Blue	−0.0844	1.1e−4	72,361	79.8	226,139
Pink	−0.0869	8.3e−5	72,900	77.1	418,724
White	−0.0799	8.9e−5	72,361	74.2	394,316

that are slightly higher than the 0.07 in Ahlfeldt et al. (2015) and find modest differences between the three collars. Pink collar workers are most sensitive to travel costs, consistent with the fact that many of these jobs are widely distributed throughout the metropolitan area. By contrast, white and blue-collar jobs are disproportionately concentrated in central and secondary business districts and in industrial areas respectively. White collar jobs are, on average, also more specialised than pink or blue-collar jobs, suggesting that this group of workers should be more heterogeneous.

It remains to separate the two components of the υ^k. For Berlin, Ahlfeldt et al. (2015) are able to independently estimate ε^k and back out a value of $\kappa \simeq 0.01$. However, as I lack the data to do this, I assume a value for κ and back out the ε_k, which I apply in the model. The former value of κ would yield ε_k well above the range of 1.3–5.6 reported in Hayakawa et al. (2021) and higher even than the 6.8 in Ahlfeldt et al. (2015). This suggests κ should take a higher value: I choose $\kappa = 0.02$, which yields ε_k equal to 4.2, 4.3 and 4.0 for blue, pink and white-collar workers respectively. Using a similar procedure, Warnes (2022) obtains values of 2.9 for high-skilled and 3.8 for low-skilled workers in Buenos Aires.[22]

[22] Warnes assumes $\kappa = 0.01$ but estimates commuting semi-elasticities below 0.05. The latter may reflect less efficient transportation and lower incomes in Buenos Aires compared to Brisbane or Berlin.

References

Ahlfeldt, G.M., Albers, T., Behrens, K., 2022. A granular spatial model. CEPR Discussion Paper No. 17126, URL: https://cepr.org/publications/dp17126.

Ahlfeldt, G., Redding, S.J., Sturm, D.M., Wolf, N., 2015. The economics of density: Evidence from the Berlin Wall. Econometrica 83 (6), 2127–2189. http://dx.doi.org/10.3982/ecta10876.

Allen, T., Donaldson, D., 2020. Persistence and path dependence in the spatial economy. NBER Working Paper No. w28059, National Bureau of Economic Research.

Anas, A., Liu, Y., 2007. A regional economy, land use, and transportation model (RELU-TRAN): Formulation, algorithm design and testing. J. Reg. Sci. 47 (3), 415–455. http://dx.doi.org/10.1111/j.1467-9787.2007.00515.x.

Australian Bureau of Statistics, 2016a. Australian census longitudinal dataset. URL: https://tablebuilder.abs.gov.au.

Australian Bureau of Statistics, 2016b. Australian statistical geography standard (ASGS): Volume 1 - Main structure and greater capital city statistical areas, cat. 1270.0.55.001.

Australian Bureau of Statistics, 2016c. Census of population and housing, 2016. URL: https://tablebuilder.abs.gov.au.

Australian Bureau of Statistics, 2016d. Employee earnings and hours (6306.0), Australia, May 2016. URL: https://www.abs.gov.au/statistics/labour/earnings-and-working-conditions/employee-earnings-and-hours-australia.

Australian Bureau of Statistics, 2019. 2016-17 Australian national accounts: input-output tables. URL: https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-input-output-tables/2016-17.

Balboni, C.A., 2021. In harm's way? Infrastructure investments and the persistence of coastal cities [Manuscript under revision]. Amer. Econ. Rev..

Bartik, A.W., Rinz, K., 2018. Moving costs and worker adjustment to changes in labor demand: Evidence from longitudinal census data. Manuscript, University of Illinois at Urbana-Champaign.

Baum-Snow, N., 2007. Did highways cause suburbanization? Q. J. Econ. 122 (2), 775–805. http://dx.doi.org/10.1162/qjec.122.2.775.

Bröcker, J., Korzhenevych, A., Schürmann, C., 2010. Assessing spatial equity and efficiency impacts of transport infrastructure projects. Transp. Res. B 44 (7), 795–811. http://dx.doi.org/10.1016/j.trb.2009.12.008.

Caliendo, L., Dvorkin, M., Parro, F., 2019. Trade and labor market dynamics: General equilibrium analysis of the China trade shock. Econometrica 87 (3), 741–835. http://dx.doi.org/10.3982/ECTA13758.

Caliendo, L., Opromolla, L.D., Parro, F., Sforza, A., 2021. Goods and factor market integration: a quantitative assessment of the EU enlargement. J. Polit. Econ. 129 (12), 3491–3545. http://dx.doi.org/10.1086/716560.

Caliendo, L., Parro, F., Rossi-Hansberg, E., Sarte, P.-D., 2018. The impact of regional and sectoral productivity changes on the US economy. Rev. Econom. Stud. 85 (4), 2042–2096. http://dx.doi.org/10.1093/restud/rdx082.

Costa, A.B., Zegras, C., Biderman, C., 2021. Chasing the city that cannot stop. J. Transp. Land Use 14 (1), 1075–1098.

Dibbelt, J., Strasser, B., Wagner, D., 2016. Customizable contraction hierarchies. J. Experim. Algorithm. (JEA) 21, 1–49. http://dx.doi.org/10.1145/2886843.

Donovan, S., de Graaf, T., de Groot, H.L., 2021. Estimating location choice models in Australia. In: Australian Transport Research Forum 2021. URL: http://www.atrf.info.

Duranton, G., Turner, M.A., 2011. The fundamental law of road congestion: Evidence from US cities. Amer. Econ. Rev. 101 (6), 2616–2652. http://dx.doi.org/10.1257/aer.101.6.2616.

Duranton, G., Turner, M.A., 2012. Urban growth and transportation. Rev. Econom. Stud. 79 (4), 1407–1440. http://dx.doi.org/10.1093/restud/rds010.

Eliasson, J., Savemark, C., Franklin, J., 2020. The impact of land use effects in infrastructure appraisal. Transp. Res. A Pract. 141, 262–276. http://dx.doi.org/10.1016/j.tra.2020.09.026.

Groot, S., de Groot, H.L., 2020. Estimating the skill bias in agglomeration externalities and social returns to education: Evidence from Dutch matched worker-firm micro-data. De Economist 168 (1), 53–78. http://dx.doi.org/10.1007/s10645-019-09354-w.

Guennebaud, G., Jacob, B., 2010. Eigen v3. http://eigen.tuxfamily.org.

Hayakawa, K., Koster, H.R., Tabuchi, T., Thisse, J.-F., 2021. High-speed rail and the spatial distribution of economic activity: Evidence from Japan's shinkansen.

Hunt, J.D., Kriger, D.S., Miller, E.J., 2005. Current operational urban land-use–transport modelling frameworks: A review. Transp. Rev. 25 (3), 329–376. http://dx.doi.org/10.1080/0144164052000336470.

Hunter, J.D., 2007. Matplotlib: A 2D graphics environment. Comput. Sci. Eng. 9 (3), 90–95. http://dx.doi.org/10.1109/MCSE.2007.55.

Iacono, M., Levinson, D., 2016. Mutual causality in road network growth and economic development. Transp. Policy 45, 209–217. http://dx.doi.org/10.1016/j.tranpol.2015.06.005.

Infrastructure Australia, 2021. Infrastructure market capacity. Technical Report, Infrastructure Australia.

Kasraian, D., Maat, K., Stead, D., van Wee, B., 2016. Long-term impacts of transport infrastructure networks on land-use change: an international review of empirical studies. Transp. Rev. 36 (6), 772–792. http://dx.doi.org/10.1080/01441647.2016.1168887.

Kleinman, B., Liu, E., Redding, S.J., 2021. Dynamic spatial general equilibrium. Econometrica 91, 385–424. http://dx.doi.org/10.3982/ECTA20273.

KPMG, 2021. Melbourne Airport Rail business case. Appendix 5. Demand modelling. Technical Report, URL: https://bigbuild.vic.gov.au/library/melbourne-airport-rail/business-case.

Le, H., Gurry, F., Byrne, M., Gharibnavaz, R., Wood, N., Lennox, J., 2021. The development and application of a land use, transport and economy interaction model. In: National Traffic and Transport Conference, 2021.

Levinson, D., 2008. Density and dispersion: the co-development of land use and rail in London. J. Econ. Geogr. 8 (1), 55–77. http://dx.doi.org/10.1093/jeg/lbm038.

Lowry, I.S., 1964. A model of metropolis. Oper. Res. 12 (3), 450–469.

McNally, M.G., 2007. The four-step model. In: Handbook of Transport Modelling. Emerald Group Publishing Limited, http://dx.doi.org/10.1108/9780857245670-003.

OpenStreetMap contributors, 2017. Planet dump retrieved from https://planet.osm.org. https://www.openstreetmap.org.

QGIS Development Team, 2021. QGIS geographic information system. URL: https://www.qgis.org.

Ramière, I., Helfer, T., 2015. Iterative residual-based vector methods to accelerate fixed point iterations. Comput. Math. Appl. 70 (9), 2210–2226. http://dx.doi.org/10.1016/j.camwa.2015.08.025.

Robson, E.N., Wijayaratna, K.P., Dixit, V.V., 2018. A review of computable general equilibrium models for transport and their applications in appraisal. Transp. Res. A Pract. 116, 31–53. http://dx.doi.org/10.1016/j.tra.2018.06.003.

Rogers, C., 2018. cnpy. URL: https://github.com/rogersce/cnpy.

Terrill, M., Emslie, O., Moran, G., 2020. The rise of mega-projects. Counting the costs. Technical Report, Grattan Institute.

Transport for New South Wales, 2017. Historic roads travel time data (TTDS). URL: https://opendata.transport.nsw.gov.au/dataset/historic-roads-travel-time-data-ttds.

Tsivanidis, N., 2021. Aggregate and distributional impacts of transit infrastructure: Evidence from Bogotá's TransMilenio. University of California, Berkeley.

Vickerman, R., 2008. Recent evolution of research into the wider economic benefit of transport infrastructure investments. OECD.

Waddell, P., 2011. Integrated land use and transportation planning and modelling: Addressing challenges in research and practice. Transp. Rev. 31 (2), 209–229. http://dx.doi.org/10.1080/01441647.2010.525671.

Warnes, P.E., 2022. Transport infrastructure improvements and spatial sorting: Evidence from Buenos Aires. Technical Report, Working paper.

Wegener, M., 2021. Land-use transport interaction models. In: Handbook of regional science. Springer, pp. 229–246. http://dx.doi.org/10.1007/978-3-662-60723-7_41.

Wittwer, G. (Ed.), 2012. Economic modeling of water. The Australian CGE experience. Springer, ISBN: 978-94-007-2876-9, http://dx.doi.org/10.1007/978-94-007-2876-9.

Xie, F., Levinson, D., 2010. How streetcars shaped suburbanization: a Granger causality analysis of land use and transit in the twin cities. J. Econ. Geogr. 10 (3), 453–470. http://dx.doi.org/10.1093/jeg/lbp031.