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Transport infrastructure and house prices in the long run

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ABSTRACT

We examine the effects of transport infrastructure on house prices in the OECD countries over the period 1870 to 2016. We employ both parametric and non-parametric panel data techniques that account for the non-linear and time-varying relationship between transport infrastructure and house prices. Our parametric results, which are based on newly developed panel data models that incorporate interactive fixed effects, suggest that transport infrastructure is positively associated with house prices. The non-parametric estimates suggest a time-varying relationship and that the average positive effect of transport infrastructure has been the case for most of the period we study. We also examine three channels through which transport infrastructure could influence house prices – economic growth, employment, and crime – and find that economic growth is a mechanism through which transport infrastructure transmits to house prices.

1. Introduction

Public infrastructure, including transport infrastructure, remains a significant expenditure element for many governments because it provides a useful means of influencing local and national economic activity (Farhadi, 2015; World Bank, 1994). Existing research has highlighted several mechanisms through which transport infrastructure enhances economic development. For instance, well-functioning transport systems and infrastructure promote economic growth by facilitating trade, improving the competitiveness of domestic firms, and lowering the costs to access international markets (Arvis et al., 2018; Martí et al., 2014). Beyond the impact on economic growth (see, e.g., Farhadi, 2015), transport infrastructure has been linked to several other factors. Among others, research has focused on the relationship between transport infrastructure and factors such as innovation (see, e.g., Agrawal et al., 2017), economic and spatial geography (Chandra and Thompson, 2000; Michaels, 2008) and political economy (Brinkman and Lin, 2019; Glaeser and Ponzetto, 2018). Emphasis has also been placed on the negative effects and potential negative externalities of transport infrastructure including noise, traffic, and pollution (see, e.g., Cohen and Coughlin, 2008, 2009; Dubé et al., 2013; Theebe, 2004).

We examine the relationship between transport infrastructure and house prices in the long run. While there has been considerable research interest in understanding the relationship between transport infrastructure and house prices, no study has taken into account the historical evolution of both transport infrastructure and house prices over time, and how this has contributed to the persistent increase in house prices. We contribute to the literature by examining the effects of transport infrastructure on house prices for a panel of 17 OECD countries from 1870 to 2016. Our contribution to the literature is unique in three main ways. First, we use panel data for what are now collectively the world's wealthiest nations over a period spanning almost 150 years. The use of the long historical dataset allows us to analyse the transport infrastructure-house price nexus through time starting from the periods of significant underdevelopment in transport infrastructure to the most advanced transport networks, seen in the OECD countries today. We are thus able to identify how the changes in evolution, approach to and emphasis on transport infrastructure through time have influenced house prices.

Our second contribution is to provide time-varying estimates of the relationship between transport infrastructure and house prices. For a period spanning almost 150 years, it is expected that the relationship between transport infrastructure and house prices will be complex and characterised by structural shifts, non-linearities, and time-varying volatility. Specifically, at the early stages of development when transport infrastructure begins to evolve, the associated benefits are expected to be much higher than in later stages. Consequently, arguments have been made on the diminishing returns of transport infrastructure over

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time. Here, it is argued that new infrastructure investments usually have high returns and promote specific opportunities that did not exist before. Thus, at this stage, the value of the returns or benefits tend to exceed the investment made. However, when there is an existing level of infrastructure, additional investments start to result in fewer benefits and this continues until a point of saturation (e.g., very matured transport infrastructure systems) where further investments would only yield relevant less benefits (Canning and Bennathan, 2007; Melo et al., 2013). Such trends on the impact of transport infrastructure are best modelled within a non-parametric time-varying framework that considers a long-time span like we do. Put differently, parametric models that have been used in the literature to examine the relationship between transport infrastructure and house prices will only provide average effects that cannot fully explain how the transport infrastructure-house prices relationship has evolved. To examine this time-varying relationship, in addition to newly developed interactive fixed effect parametric methods that account for endogeneity and typical issues pertaining to the use of panel data, especially over long periods like we do (Bai, 2009; Bai et al., 2009; Casas et al., 2021; Kapetanios et al., 2011), we also employ a non-parametric panel data method (see, Awaworyi Churchill et al., 2021a; Hailemariam et al., 2019; Li et al., 2011; Silvapulle et al., 2017). The use of the non-parametric method allows us to capture potential non-linearities by allowing for the estimate of the effects of transport infrastructure on house prices to vary across countries and over time with unknown functional form. This allows us to understand if the returns to transport infrastructure diminish over time.

Third, we contribute to the literature by providing empirical evidence on the mechanisms through which transport infrastructure transmits to house prices. The existing literature, as discussed in Section 2, has suggested several mechanisms through which transport infrastructure could influence house prices. These mechanisms determine whether the relationship between transport infrastructure is positive or negative, and can help shed light on the conflicted relationship. We examine economic growth, employment, and crime as mechanisms through which transport infrastructure transmits to house prices. We consider these three mechanisms for two main reasons. First, little attention has, however, been given to exploring these mechanisms, although conceptually, there is reason to believe that these are potential mechanisms. Second, as a practical consideration, historical data is available for these variables thus allowing us to examine them in the context of our empirical analysis.

Our interactive fixed effect parametric estimates suggest that transport infrastructure is positively associated with house prices. The non-parametric estimates also support this finding, and while we find evidence of a time-varying non-linear relationship, the relationship has been positive for most of the period we study. We find that economic growth is a channel through which transport infrastructure transmits to house prices.

We contribute to several strands of literature. The first, which are the closest in the literature to ours, are studies that have examined the direct effect of transport infrastructure on house prices, housing demand and investments (Cao and Porter-Nelson, 2016; Dorantes et al., 2011; Efthymiou and Antoniou, 2013; Jayantha et al., 2015; Laakso, 1992). These studies find that transport infrastructure generally has positive impacts on prices of houses in close proximity (Cao and Porter-Nelson, 2016; Jayantha et al., 2015; Laakso, 1992). We differ from these studies given that we do not focus on the impact of proximity to a transport system on house prices but rather on the impact of transport infrastructure over a longer period on house prices in a cross-country setting. Additionally, most of the previous studies consider case studies using data from single cities within a country, thus, limiting generalizability.

Second, our study is also related to those that have examined the impact of transport infrastructure on various factors that serve as potential mechanisms through which transport infrastructure influences house prices. This literature has examined the effects of transport infrastructure on outcomes such as economic growth, employment growth, crime, and pollution, all of which have been linked to house prices (see, e.g., Awaworyi Churchill et al., 2020; Awaworyi Churchill et al., 2021b; Farhadi, 2015; Gong and Wheeler, 2002; Hensher et al., 2012; Mejia-Dorantes et al., 2012; Padeiro, 2013; Rubin and Segal, 2015; Shenggen and Zhang, 2004). We contribute to this strand of literature by examining economic growth, employment, and crime as mechanisms through which transport infrastructure transmits to house prices over the long term.

Third, there is also a strand of literature that has examined the impact of infrastructure development on changes in accessibility, which has significant implications for housing demand (Dorantes et al., 2011; Dubé et al., 2013; Efthymiou and Antoniou, 2013; Hoogendoorn et al., 2019; Martínez and Viegas, 2009; Mitra and Saphores, 2016; So et al., 1997). We differ from these studies as our focus is not on either change in accessibility or housing demand. We focus on house prices and examine the direct effects of transport infrastructure on house prices. We also explore several channels, other than accessibility, through which transport infrastructure transmits to house prices.

The rest of the paper is organized as follows. Section 2 discusses the conceptual relationship between transport infrastructure and house prices as well as the transmission channels. Section 3 presents the data and empirical methods. Section 4 presents the empirical results. Section 5 concludes.

2. Why do transport infrastructure investments influence house prices?

The relationship between house prices and transport infrastructure investments is not new (Alonso, 1964). Theoretically, the effect of transport infrastructure on house prices can either be direct or indirect via various channels. The relationship could be negative or positive, depending on the channel of transmission.

2.1. Direct effects

Transport infrastructure can influence house prices by directly altering the dynamics of demand and supply in the housing market. One of the well-known explanations of a direct relationship is that transport infrastructure relaxes the constraints imposed by geographic mobility barriers, thus improving access to various services and amenities. Some traditional household location theories suggest that accessibility impacts on house prices given those who live closer to transport networks have lower costs of commuting to places of employment and would, therefore, pay a premium for such locations (Mills, 1967; Muth, 1969; Straszhem, 1987). Put differently, households are willing to pay higher prices for houses located in places with ease of accessibility that can facilitate economic mobility (So et al., 1997). This willingness to pay tends to put upward pressure on house prices. Similarly, the expectation of new transport infrastructure or improvements to existing transport networks in an area tends to make the immediate or surrounding neighbourhoods more attractive to households (Jayantha et al., 2015; Laakso, 1992). This results in upward pressure on housing demand that increases house prices (Dorantes et al., 2011; Dubé et al., 2013; Efthymiou and Antoniou, 2013; Hoogendoorn et al., 2019; Martínez and Viegas, 2009; Mitra and Saphores, 2016).

The direct effect of transport infrastructure via housing demand need not always lead to a positive relationship with house prices. In particular, transport infrastructure could cause slower growth in some areas, decreasing land values and house prices (Brinkman and Lin, 2019). By increasing housing demand in certain areas, transport infrastructure can significantly depress demand in other areas when households relocate away. The net effect of transport infrastructure on house prices then lies in weighing the increase and decrease in demand in housing over time and the corresponding induced changes in price.

Transport infrastructure is associated with an increase in housing supply. Building activity increases in anticipation of transport infrastructure investments (Cao and Porter-Nelson, 2016), which depresses house prices (Wong et al., 2019). In addition, when house price increase induced by housing demand is sufficiently large, it generates a surge in property investment and development decisions given that housing investments are a function of property values (Edelstein and Tsang, 2007). New housing development increases the supply of housing.

Further, as households move to new locations with improved accessibility due to transport infrastructure investments, developers supply new housing to meet the potential demand. This causes housing supply to increase, holding other factors constant. Thus, the added interconnectivity provided by the development of transport infrastructure tends to increase the supply of residential property (Srinurak and Mishima, 2017). Such an increase in supply, holding demand constant, will place downward pressure on house prices.[1]

2.2. Effects via mechanisms

Indirectly, transport infrastructure can have a positive effect on house prices via its effects on employment and economic growth, and a negative impact by generating negative externalities. We discuss these in turn.

Transport infrastructure is positively related to employment growth (de Vor and de Groot, 2010; Jiwattanakulpaisarn et al., 2009; Padeiro, 2013; Pereira and Andraz, 2005). Transport infrastructure influences the location choice of firms such that firms tend to cluster around areas with developed infrastructure (Anas et al., 1998), which creates or increases employment opportunities in locations with higher investments in transport infrastructure. This is more so the case for firms involved in manufacturing, wholesale trade and logistics (Bowen, 2008). Employment is an important factor in determining house prices as it increases households' expectation of higher wage growth and reduces uncertainty surrounding future income stability and capacity to repay debt (Jacobsen and Naug, 2005; Szumilo et al., 2017). With higher employment rates, the predisposition to purchase owner-occupied dwelling as well as investment in residential property increases, thereby increasing demand for housing and upward pressure on house prices.

Transport infrastructure is positively related to economic growth (Farhadi, 2015), which is an important determinant of house prices (Leung, 2003). Transport infrastructure removes geographic barriers by providing good connectivity that enhances economic mobility relevant to the production and distribution of goods and services. By removing such geographic barriers, labour markets become more efficient, thus, enhancing productive capacity and growth (Graham, 2014). Related to this, transport infrastructure influences income inequality (Rubin and Segal, 2015; Shenggen and Zhang, 2004), and through this mechanism, can influence house prices. Income inequality leads to the clustering of the rich in attractive neighbourhoods with high house prices beyond the means of low-income households (Chen et al., 2012b; Gingrich and Ansell, 2014; Scarpa, 2015), thus, leaving the poor in less desirable neighbourhoods with further depressed house prices (Lupton and Power, 2004). The net clustering effect due to income inequality is the average of increases in house prices in attractive neighbourhoods and decreases in less desirable neighbourhoods.

Transport infrastructure could indirectly affect house prices negatively through externalities (Dubé et al., 2013; Henneberry, 1998), including noise pollution, air pollution, traffic and crime (Cohen and Coughlin, 2008, 2009; Efthymiou and Antoniou, 2013; Ridker and Henning, 1967; Theebe, 2004). The creation of train stations as part of transport infrastructure investments creates access to neighbourhoods for criminals, thus, increasing crime rates (Bowes and Ihlanfeldt, 2001; Linden and Rockoff, 2008), which have been found to have a negative relationship with house prices (Besley and Mueller, 2012; Tita et al., 2006). Specifically, crime rates have an impact on the perception of safety in a neighbourhood. Perceived level of security in a neighbourhood fundamentally affects the quality of a neighbourhood (Gallimore et al., 1996). As crime rates increase, perceived security and quality of a neighbourhood deteriorates, and residents choose to relocate to more secured neighbourhoods (Hailemariam et al., 2021; Morenoff et al., 2001). The effect is decreased demand for housing relative to supply, leading to a fall in property values as opposed to property values in neighbourhoods with perceived high levels of security. In contrast, McIntosh et al. (2018) found that local infrastructure investments in low-income urban neighbourhoods reduced crime rates and increased house prices.

2.3. Hypothesis and net effects at the country-level

The preceding discussions on the relationship between transport infrastructure and house prices suggest that transport infrastructure tends to increase house prices by increasing demand for housing. However, depending on the channel of influence, it might depress housing demand in neighbouring areas, and thus house prices in such areas. At the country level, one might expect these positive and negative effects of transport infrastructure on house prices to cancel out. However, evidence from the empirical and theoretical literature generally suggests a net increase in house prices (Hou and Li, 2011; Rokicki and Stępniak, 2018; So et al., 1997; Vickerman, 2008). Specifically, the price effects of transport infrastructure will only cancel out if the price decrease in negatively affected areas is symmetric with the price increase in regions that benefit from transport infrastructure.

The potential exists for transport infrastructure in an area to generate positive externalities in nearby areas, such that even though people tend to move towards areas with better infrastructure development, the positive externalities would cause increases, rather than decreases, in nearby areas where people migrate from (Meen, 1999; Yu et al., 2013). Consequently, the price increase related to transport infrastructure in an area, coupled with associated price increases in neighbouring areas, caused by positive externalities, is likely to offset any price decline. This generates a net positive effect of transport infrastructure on house prices. Put differently, there are interregional transmission shocks of house prices or positive externalities resulting from transport infrastructure in nearby regions that cause house prices of closely related regions to correlate. Therefore, house price increases in one region due to improved transport infrastructure and accessibility tend to transmit to other areas and offset any potential decline in house prices, thereby leading to overall growth in aggregate house prices in a country (Meen, 1999).

More generally, transport infrastructure development improves on spatial accessibility at the national level, and such improvements offer access to markets for trades and investments in firms and housing, which increases house prices (Hou and Li, 2011; Rokicki and Stępniak, 2018; So et al., 1997; Vickerman, 2008).

Overall, the preceding discussions on the conceptual relationship between transport infrastructure and house prices, leads us to expect that:

Hypothesis. Cross-country differences in transport infrastructure can explain differences in house prices.

2.4. Connecting with existing conceptual models

The discussions so far allow us to appropriately connect with the conceptual literature on house price determination. In particular, we focus on Archer and Ling (1997) who proposed a three-dimension

[1] While this may suggest within country dynamics, it is important to note that national house prices reflect the average house prices across the sub-national locations within a country. Thus, the dynamics of demand and supply at the sub-national level are very instrumental in determining national house prices, and consequently, cross-country differences in house prices.

housing market model for house price determination. We leverage that to develop our conceptual framework in explaining the overall changes in house prices due to variations in transport infrastructure investments in a country. The housing market could be sub-divided into space, property, and capital markets that interact to determine house prices. Transport infrastructure investments, indirectly through economic factors (i.e., economic growth and employment), affect household incomes and business activities, consequently increasing or decreasing demand for space (or dwellings) in the housing market. Specifically, as household income changes as a result of changes in economic growth and employment, it affects the number of households capable of purchasing a house, consequently increasing or decreasing demand for space (or dwellings) in the housing market.

Similarly, capital market factors in the form of interest rates impact market conditions to determine whether households and construction firms would borrow for home purchases and housing construction, respectively. This is consistent with the idea that higher interest rates affect the cost of borrowing and therefore influence the supply and demand dynamics in the housing market. As a result, depending on market conditions (e.g., levels of interest rate, and inflation), households and construction firms would decide whether to borrow to purchase and supply houses, respectively. This interaction between the space and capital markets results in an upward or downward push in house prices in the housing market.

Importantly, the space and capital market dimensions are influenced by government policies given that they play important roles in determining investments and market conditions. The expected dynamic relationship between transport infrastructure and house prices is accordingly depicted in Fig. 1. Given the scope of the current study, and data-related issues, we are, however, unable to fully explore all the dimensions shown in Fig. 1. Specifically, we are not able to incorporate direct measures of market conditions and government policy in our analysis. The inability to model all relationships that conceptually exist is likely to generate omitted variable bias, which could either lead to overestimation or underestimation of the true effect of transport infrastructure. We, however, address this potential bias within our interactive fixed effect framework.

3. Data and empirical framework

3.1. Empirical model

To investigate the relationship between transport infrastructure stock and house prices, we specify the following model:

$$HP_{it} = \lambda_0 + \lambda_1 INFR_{it} + \lambda_2 GDP_{it} + \lambda_3 POP_{it} + \lambda_4 ML_{it} + \lambda_5 NML_{it} + \lambda_6 IR_{it} + \lambda_7 INFL_{it} + v_{it} \tag{1}$$

where subscripts i and t denote country and year, respectively. The dependant variable, *HP*, is real house prices, constructed as nominal house prices adjusted by the CPI index. *INFR* denotes transport infrastructure, and thus the parameter of interest is λ_1 which captures the effect of transport infrastructure on house prices.[2] The control variables include real GDP per capita (*GDP*), population (*POP*), mortgage loans to GDP ratio (*ML*), non-mortgage loans to GDP (*NML*), the interest rate (*IR*) and inflation (*INFL*). v_{it} is the error term.

GDP is the most commonly used measure of a country's economic wellbeing, and has been found to be correlated with house prices (see, e.g., Leung, 2003; Otto, 2007). Population is an important factor that determines trends relating to the demand and supply of housing, and is therefore often included as a control variable in house price regressions to control for demographic factors as well as potential trends relating to demand and supply (see, e.g., Day, 2018; Engelhardt and Poterba, 1991; Miles, 2012). Mortgage loans to GDP ratio is often used as a proxy for housing investment and credit supply in an economy, while non-mortgage loans is a proxy for financial development (Adelino et al., 2012; Carbó-Valverde and Rodriguez-Fernandez, 2010; Fitzpatrick and McQuinn, 2007). We also control for interest rate and inflation given that they influence market trends and household ability to finance their homes (Anari and Kolari, 2002; Kuang and Liu, 2015; McQuinn and O'Reilly, 2008; Tang and Tan, 2015; Xu and Tang, 2014).

In estimating equation (1), we employ the following interactive fixed effects structure for the error term:

$$v_{it} = f_t^{'}\lambda_i + \varepsilon_{it} \tag{2}$$

where $f_t^{'}\lambda_i$ is consistent with the factor structure as in Pesaran (2006) and Bai (2009), and ε_{it} is a random error term.

Panel data with interactive fixed effects have been significantly researched and applied in the literature in various contexts (see, e.g., Bai et al., 2009; Casas et al., 2021; Kapetanios et al., 2011). We follow the three-step estimation approach in Casas et al. (2021).

3.2. We rewrite equation (1) as

$$Y_{it} = X_{it}^{'}\beta_0 + \lambda_i^{'} f_t + \varepsilon_{it} \tag{3}$$

where Y_{it} is house prices, X_{it} is a vector containing the relevant control variables including transport infrastructure. According to Casas et al. (2021), the estimation involves three steps which begins by writing equation (3) in matrix form as follows.

$$Y_i = X_i\beta_0 + F\,\lambda_i + \varepsilon_i \tag{4}$$

where $Y_i = (Y_{i1}, \ldots, Y_{iT})^{'}$, $F = (f_1, \ldots, f_T)^{'}$ and the other variables are defined conformably.

Step 1:

3.2.1. Obtain an initial estimate by

$$\left(\widetilde{\beta}, \widetilde{F}\right) = \underset{b\in\mathbb{R}^d, F\in D_F}{\mathbf{argmin}} \sum_{i=1}^{N} (Y_i - X_i\beta)^{'M_F}(Y_i - X_i\beta) = \underset{\beta\in\mathbb{R}^d, F\in D_F}{\mathbf{argmin}}\, Q(\beta, F),$$

where $D_F = \left\{F \middle| \frac{1}{T}F^{'}F = I_J, J \geq r\right\}$, and J is a user chose large constant.

Step 2:

Let $\widetilde{\eta}_j$ be the jth largest eigenvalue of the sample covariance matrix

$$\widetilde{\sum} = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - X_i\widetilde{\beta}\right)\left(Y_i - X_i\widetilde{\beta}\right)^{'}$$

Define a mock eigenvalue $\widetilde{\eta}_0 := \frac{1}{N}\sum_{i=1}^{N} \| Y_i - X_i\widetilde{\beta}\|^2$, and estimate r by

$$\widetilde{r} = \underset{0\leq\ell\leq J}{\mathbf{argmin}} \left\{ \frac{\widetilde{\eta}_{\ell+1}}{\widetilde{\eta}_\ell} \cdot \mathbb{I}\left(\frac{\widetilde{\eta}_\ell}{\widetilde{\eta}_0} \geq \varepsilon_N\right) + \mathbb{I}\left(\frac{\widetilde{\eta}_\ell}{\widetilde{\eta}_0} < \varepsilon_N\right) \right\}$$

where $\varepsilon_N = \{\ln(\max\{\widetilde{\eta}_0, N\})\}^{-1}$.

[2] While our outcome variable *HP* captures house prices, our focus is on changes (i.e., increase or decrease) in house prices due to transport infrastructure, which would be captured by λ_1. Here, a positive value for λ_1 would be interpreted as transport infrastructure causing house price increases, on average. This basically reflects increases in the average house price that can be linked with transport infrastructure, ceteris paribus.

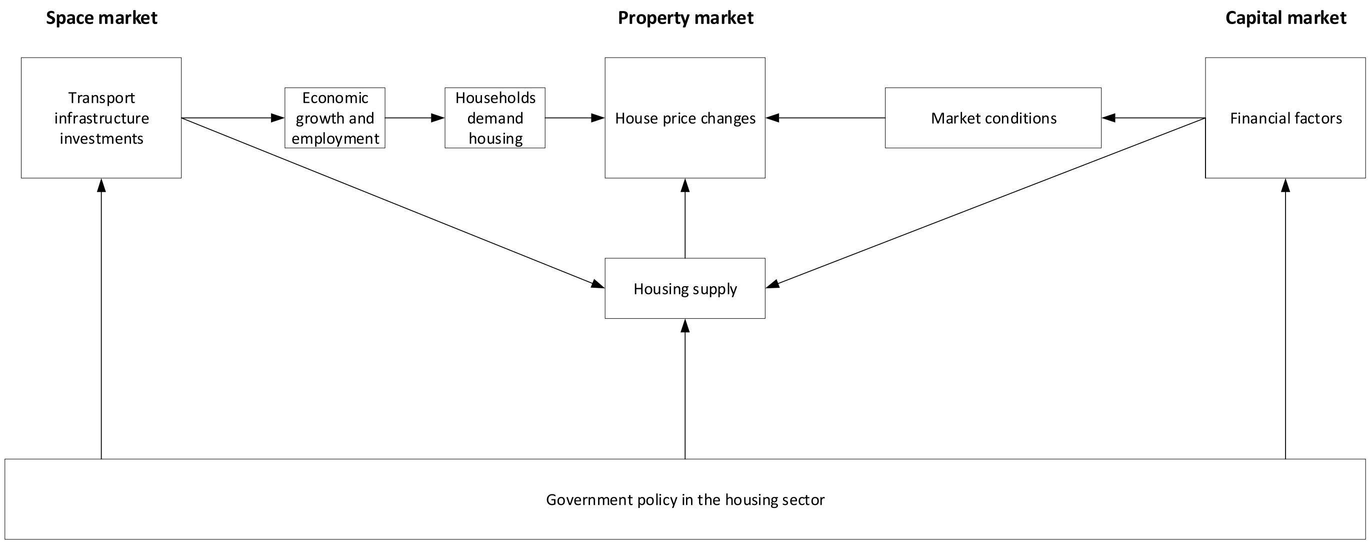

Fig. 1. Conceptual model on house prices. Source: Adapted from Archer and Ling (1997).

Step 3:

Update D_F by $D_F = \left\{ F \middle| \frac{1}{T} F' F = I_{\tilde{r}} \right\}$, and then update the estimate by $(\tilde{\beta}, \tilde{F}) = \mathbf{argmin}_{\beta \in \mathbb{R}^d, F \in D_F} Q(\beta, F)$.

The interactive fixed effect model has several benefits compared to the traditional fixed effect model. First, the interactive fixed effect model nests the individual fixed effects and time fixed effects. Thus, in our case, the traditional individual fixed effect (α_i) plus time fixed effect (γ_t) would be nested as $f_t'\lambda_i = (1, \gamma_t)(\alpha_i, 1)'$ and allows more flexibility for $f_t'\lambda_i$. In order to account for omitted variable bias, the traditional fixed effect model incorporates individual (i.e., country) and time fixed effects, which control for unobserved country characteristics and potential shocks that emerge over time. However, the traditional fixed effect model only controls for unobserved characteristics across time and countries independently, thus ignoring the potential interaction between countries and time, which can be a source of bias. The interactive fixed effect model addresses this concern by controlling for the interaction between countries and time in addition to the standard control for country and time fixed effects independently.

Second, the interactive fixed effect model takes into account cross-sectional dependence (CSD) between regressors and residuals (Bai, 2009). The traditional approach for panels that have long time span is usually characterised by a series of tests, such as testing for CSD and panel unit roots, prior to model estimation. The interactive fixed effect model takes into account these typical issues, and allows us to capture CSD among countries without relying on multiple tests and estimations.

Third, the interactive fixed effect model takes a principal component-based approach that allows the unobservable factor structure to be correlated with regressors, thus, accounting for endogeneity (Bai, 2009; Pesaran, 2006).

For our baseline results, we estimate equation (1) using the standard parametric panel fixed effect model, while our main parametric results are based on the interactive fixed effect model.

3.3. Data

Our historical dataset consists of annual observations for a panel of 17 high income OECD countries over the period 1870 to 2016. The 17 OECD countries are: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom (UK), and the United States (US). Consistent with the literature, we measure transport infrastructure endowment as the stock of infrastructure rather than infrastructure flow (see, e.g., Awaworyi Churchill et al., 2021a; Farhadi, 2015; Irmen and Kuehnel, 2009; Sutherland et al., 2009). ***INFR***, which is sourced from Farhadi (2015), captures roads, highways, railways, airports and inland waterways, and is a measure of infrastructure stock calculated using the perpetual inventory method with an assumed 2 per cent depreciation rate. Specifically, the value of different transport infrastructure investments as a share of GDP is used to calculate the stock of transport infrastructure using the perpetual inventory method following the formulae $k_{it} = I_{it} + (1 - \delta)k_{i,t-1}$ where I_{it} investment as a share of GDP and δ is the assumed 2 per cent depreciation rate. The initial capital stock is derived by dividing the initial infrastructure investment by the sum of the depreciation rates and the average annual infrastructure investment growth rate over the entire data period. This is demonstrated mathematically as $(i_0 / (\delta + g))$.

Data on real GDP per capita (*GDP*) and population (*POP*) are sourced from the Maddison Project Database (Inklaar et al., 2018). In the literature on international comparisons, real GDP per capita is used for comparisons of income levels across countries. 'real' refers to the series which are based on a common set of prices across countries. In Inklaar et al. (2018), this variable is expressed in 1990 USD by correcting for inflation in the US to provide magnitudes that are comparable over time. Thus, this measure could closely reflect direct historical income comparisons. Data on house prices are from Knoll et al. (2017). Using more than 60 different sources and combining existing and unpublished data, Knoll et al. (2017) constructed a novel dataset that covers house prices for 14 advanced economies over the period 1870 to 2012. Using same methodology and following same sources, Jordà et al. (2017) conducted two updates: first, include more countries; and second, update the series to 2016.[3] We deflate the house prices with Consumer Price Index (CPI) to obtain real house prices (*HP*).

The CPI, interest rate, mortgage and non-mortgage loans are from the Jordà-Schularick-Taylor Macrohistory Database (Jordà et al., 2017).[4] This database provides comprehensive coverage of long-run macroeconomic and financial data for the 17 OECD countries since

[3] For the sources, compilation, and methodology on house prices series, see Knoll et al. (2017).

[4] Available at http://www.macrohistory.net (accessed on 29 June 2020, version R4). Table 1 presents summary statistics for the variables used.

1870.[5] The underlying data is obtained from a very broad range of sources, including historical economic and financial studies, statistical yearbooks, journal articles and central banks as well as central and private bank archives. Inflation (*INFL*) is measured as change in CPI. To get non-mortgage loans, we subtract mortgage loans from total loans. Then, we construct *ML* (mortgage loans as a proportion of GDP) and *NML* (non-mortgage loans as a proportion of GDP).

Although the use of historical data has important benefits, data quality issues are also of concern. The economic history literature has demonstrated that issues with data quality in the context of long-run historical datasets are to be expected if countries transition from low to advanced financial systems, which has been the case for most countries following World War II (Awaworyi Churchill et al., 2018). However, it has been found that such data quality issues often pertain to non-OECD countries, which is not the case for us given that we focus on OECD countries (Johnson et al., 2013, p. 273). In contrast to non-OECD countries, most OECD countries had relatively advanced accounting, financial and reporting systems during the first globalization boom, which allow for comparability of estimates (Awaworyi Churchill et al., 2018; Madsen et al., 2018), and thus, data reliability is not a problem here.

4. Results

4.1. Parametric results

In Table 2, we present parametric results for the relationship between transport infrastructure and house prices. In Column (1), we report a standard fixed effect model that only controls for time fixed effects. Column (2) displays results for the same model but controls for only country fixed effects, while Column (3) controls for both country and time fixed effects. Column (4) reports results from our preferred model, which in addition to country and year fixed effects, also controls for interactive fixed effects. Across all four columns, transport infrastructure is positively associated with real house prices. Depending on the model, a one per cent increase in transport infrastructure as a share of GDP is associated with a 0.088–0.938 per cent increase in real house prices.

The coefficient on transport infrastructure from our preferred model, which controls for endogeneity is 0.088. This is the smallest effect size and suggests that a one per cent increase in transport infrastructure as a share of GDP generates a 0.088 per cent increase in real house prices. Taking into account the magnitude of the coefficient of transport infrastructure in the interactive fixed effect model compared to the other fixed effect models, we find evidence of upward bias in the standard fixed effect model. That the interactive fixed effects model accounts for endogeneity is an indication that endogeneity generates upward bias in the standard fixed effect models. However, the positive effect of transport infrastructure on house prices is robust across each model, a finding that is consistent with the previous literature that has examined the impact of proximity to a transport system on house prices (Cao and Porter-Nelson, 2016; Dorantes et al., 2011; Efthymiou and Antoniou, 2013; Jayantha et al., 2015; Laakso, 1992).

In our preferred model (Column 4), the results for the control variables are consistent with the literature and show that GDP per capita is positively related to house prices (see, e.g., Égert and Mihaljek, 2007;

Table 1
Summary statistics.

Variable	Description	Mean	Std. Dev.	Min.	Max.
Real house prices (HP)	Real house prices	−1.014	2.656	−26.974	1.274
Transport infrastructure (INFR)	Transport infrastructure stock as a percentage of GDP	−0.161	2.021	−5.090	6.149
GDP per capita (GDP)	GDP per capita (1990 USD)	8.674	0.921	6.609	10.412
Population (POP)	Population	16.530	1.251	14.331	19.598
Mortgage loans-to-GDP (ML)	Mortgage loans to GDP ratio	−2.476	3.061	−33.632	0.384
Non-mortgage loans-to-GDP (NML)	Non-mortgage loans to GDP ratio	−1.357	1.397	−9.400	9.471
Interest rate (IR)	Long term interest rate	1.580	0.526	−3.349	3.166
Inflation (INFL)	Inflation measured as change in CPI	1.132	1.882	−5.997	17.415
Employment (EMP)	Economy-wide employment	2.237	0.377	0.992	3.681
Robberies (ROB)	Robberies per 100,000 people	4.967	7.003	−11.591	45.857

Notes: we take the log of all variables.

Table 2
Parametric results.

	Dependent variable: real house prices			
	(1)	(2)	(3)	(4)
INFR	0.333***	0.671***	0.938***	0.088**
	(0.031)	(0.105)	(0.097)	(0.006)
	[0.272, 0.393]	[0.466, 0.876]	[0.747, 1.128]	[0.076, 0.101]
GDP	2.554***	0.465***	3.414***	0.238**
	(0.295)	(0.120)	(0.326)	(0.018)
	[1.975, 3.134]	[0.229, 0.701]	[2.775, 4.053]	[0.206, 0.278]
POP	−0.263***	0.158	1.623***	−0.121**
	(0.056)	(0.109)	(0.186)	(0.010)
	[-0.373, −0.154]	[-0.056, 0.372]	[1.258, 1.988]	[-0.143, −0.104]
ML	0.145***	0.242***	0.283***	0.187**
	(0.045)	(0.036)	(0.038)	(0.016)
	[0.057, 0.234]	[0.171, 0.312]	[0.208, 0.359]	[0.154, 0.216]
NML	0.181*	0.360***	0.469***	−0.015
	(0.106)	(0.088)	(0.089)	(0.031)
	[-0.026, 0.389]	[0.187, 0.533]	[0.294, 0.644]	[-0.089, 0.035]
IR	−0.099	−0.124	−0.076	−0.246**
	(0.152)	(0.086)	(0.158)	(0.027)
	[-0.397, 0.200]	[-0.293, 0.046]	[-0.385, 0.234]	[-0.299, −0.194]
INFL	0.037*	−0.121***	−0.061*	0.080**
	(0.022)	(0.029)	(0.032)	(0.007)
	[-0.006, 0.079]	[-0.177, −0.065]	[-0.124, 0.003]	[0.065, 0.093]
Country FE	No	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes
Interactive FE	No	No	No	Yes
Observations	2482	2482	2482	2482

Column (1) reports results that include time FEs but without country and interactive FEs.
Column (2) reports results that include country FEs but without time and interactive FEs.
Column (3) reports results that include country and time FEs but without interactive FEs.
Column (4) reports results that include country, time and interactive FE.
Notes: Standard errors reported in parentheses. 95 per cent confidence intervals reported in brackets. ***, **, and * indicate statistical significance at the 1 per cent, 5 per cent, and 10 per cent levels, respectively.

[5] Interested readers are referred to Jordà-Schularick-Taylor Macrohistory Database (Jordà et al., 2017) for more details. The database could be accessed at https://www.macrohistory.net/database/.

Leung, 2003), while the effect of population is negative (see, e.g., Filipa, 2015). Mortgage loans to GDP is positively related to house prices indicating that housing demand or investment proxied by the increase in mortgage loans increases house prices. We also find a negative association between interest rate and house prices; a positive association between inflation and house prices; and an insignificant relationship between non-mortgage loans-to-GDP ratio and house prices.

4.2. Sensitivity checks on parametric results

We conduct a number of checks to examine the robustness of our parametric results. These checks involve the use of alternative panels. First, we examine the robustness of our results to the use of a five-year non-overlapping intervals panel. Madsen et al. (2018) recommend the use of this panel to address a potential bias that may be associated with the use of interpolated data. Given that in the construction of some of the variables used in our analysis, some missing values were interpolated, although minimally, to achieve a balanced panel, we conduct this check to ensure that our results are robust.

Second, we also examine the robustness of our results to an alternative panel construction using five-year moving averages. In addition to addressing potential bias from interpolated data, the use of five-year moving averages also has potential benefits of eliminating randomness or abrupt change in trends that may be reported for any variable and allowing for the estimation of coefficients that take into account trend cycles.

Third, we examine the sensitivity of our results to the use of a panel constituting only the Group of Seven (G7) countries, which had a limited number of missing observations and, thus, did not require many interpolations. Table 3, which reports the results for the alternative panels, shows that the positive effect of transport infrastructure on house prices is robust. Specifically, depending on the specification, we find that a one per cent increase in transport infrastructure stock is associated with 0.076–0.084 per cent increase in the real house prices.

In a final check, we examine the sensitivity of our results to the exclusion of various covariates that are likely to increase multicollinearity in our model. To this end, in Table 4, we report results from regressions that exclude mortgage loans and inflation from our model. Given that house prices are deflated using CPI, the inclusion of inflation as a covariate may be considered redundant. Similarly, given the strong correlation between mortgage loans and house prices, as case can be made for its exclusion. In Table 4, we find that our results remain robust with the exclusion of these variables.

4.3. Non-parametric results

We estimated equation (1) using parametric methods, however, given that our dataset spans almost one and half centuries, we expect the relationship between transport infrastructure and house prices to be more complex, characterised by non-linearities, time-varying volatility and structural shifts resulting from the multiple recessions and world wars over the period. The results from the parametric model only provide an average effect that does not take into account the time-varying nature of the transport infrastructure-house price relationship. Thus, we extend our analysis to model the relationship between transport infrastructure and house prices non-linearly using a state-of-the-art non-parametric model that allows the coefficient on transport infrastructure to vary over time with unknown functional form.

We modify equation (1) and assume that the log differences of transport infrastructure, the control variables and a time trend can explain the log of house prices. The non-parametric model is expressed as:

$$\ln HP_{it} = f_i(\mathrm{t}) + \lambda_1(t)\Delta \ln INFR_{it} + \lambda_2(t)\Delta \ln GDP_{it} + \lambda_3(t)\Delta \ln POP_{it} + \lambda_4(t)\Delta \ln ML_{it} + \lambda_5(t)\Delta \ln NML_{it} + \lambda_6(t)\Delta \ln IR_{it} + \lambda_7(t)\Delta \ln INFL_{it} + \alpha_i + u_{it}, \tag{3}$$

where Δ is the difference operator; $f_i(t) = f_i\left(\frac{t}{T}\right)$, for $i = 1, 2, \ldots, N$ represents unknown individual trend functions; $\lambda_j(\mathrm{t}) = \lambda_j\left(\frac{t}{T}\right)$, for $j = 1, 2, \ldots, N$, denote time-varying coefficients; α_i is an unknown individual component; and u_{it} is stationary for each i. For identification purposes, we assume that $\sum_{i=1}^{N} \alpha_i = 0$.

The trend and coefficient functions can be estimated non-parametrically using the LLDVE method (Chen et al., 2012a). The LLDVE method works with the assumption that $f\left(\frac{t}{T}\right) = f_i\left(\frac{t}{T}\right)$ for all i, which is a common trend, while individual trend functions can be estimated using fitted residuals following Phillips (2001)..[6]

Table 3
Robustness checks (different samples).

	5 year period	5 year moving average	G7
	(1)	(2)	(3)
INFR	0.083**	0.084**	0.076**
	(0.013)	(0.006)	(0.008)
	[0.057, 0.110]	[0.074, 0.096]	[0.061, 0.091]
Other controls	Yes	Yes	Yes
Interactive FE	Yes	Yes	Yes
Observations	510	2414	1022

Notes: Numbers in parentheses and brackets are standard errors and 95 per cent confidence intervals based on 999 replications using wild bootstrap. All estimations include the relevant control variables as in Column (4) of Table 2. ** indicates statistical significance at the 5 per cent level.

Table 4
Robustness checks (different covariates).

	Dependent variable: real house prices	
	(1)	(2)
INFR	0.103**	0.085**
	(0.006)	(0.006)
	[0.092, 0.114]	[0.074, 0.096]
GDP	0.287**	0.407**
	(0.018)	(0.015)
	[0.253, 0.327]	[0.380, 0.438]
POP	−0.147**	−0.217**
	(0.010)	(0.008)
	[-0.170, −0.13]	[-0.235, −0.202]
NML	0.009	0.135**
	(0.031)	(0.028)
	[-0.060, 0.059]	[0.073, 0.185]
IR	−0.138**	−0.190**
	(0.022)	(0.019)
	[-0.182, −0.096]	[-0.230, −0.151]
ML	0.202**	
	(0.016)	
	[0.171, 0.232]	
Country FE	Yes	Yes
Time FE	Yes	Yes
Interactive FE	Yes	Yes
Observations	2482	2482

Columns (1) report results for regressions that exclude mortgage loans.
Columns (2) report results for regressions that exclude mortgage loans and inflation.
Notes: Numbers in parentheses and brackets are standard errors and 95 per cent confidence intervals based on 999 replications using wild bootstrap. ** indicates statistical significance at the 5 per cent level.

[6] For the technical details and recent application of the LLDVE method in other contexts, see, Silvapulle et al. (2017), Hailemariam et al. (2019), Awaworyi Churchill et al. (2019), Liddle et al. (2020) and Uddin et al. (2020).

Figs. 2–5 report the non-parametric results. Fig. 2 reports the estimates of the time-varying trend of house prices, while Fig. 3 reports the time-varying estimates of transport infrastructure. The estimates of the control variables are reported in Fig. 4. Fig. 5 reports results for the country-specific and common trends, which account for non-linearity and heterogeneity over time. In Figs. 2–4, the solid blue line represents the coefficient estimates, while the red dashed lines denote the 95% confidence intervals. In all the Figures, the Y-axis reports the range of estimates or coefficients while the X-axis reports the year.

Fig. 2 shows a persistent increase in the common trend in real house prices since the beginning of the sample period. It steadily increased between 1870 and 1913, which is around first globalisation wave, and remained relatively stable throughout the inter-war and Great Depressions periods. Knoll et al. (2017) link the increase in real house prices over this period to the transport revolution in the late 19th and early 20th century. As transport costs flattened over the second half of the 20th century, land behaved like a 'fixed factor' (Knoll et al., 2017, p. 44). The relatively steep increase in house prices between 1950 and 1980 can be linked to the expenditure for housing services, which, over the post-WWII period, grew faster than income (Knoll et al., 2017, p. 44).

Fig. 3 shows that the relationship between transport infrastructure and house prices is time-varying and that the elasticity of transport infrastructure is statistically significant and positive for most of the sample period. This is consistent with the average positive effect found in the parametric analysis. Specifically, we find transport infrastructure is positively related to house prices between 1870 and the late 1800s. This is consistent with Knoll et al. (2017)'s assessment of increased house prices being linked with the transport revolution. The Second Industrial Revolution, starting in the late 19th century, was characterised by an increase in infrastructure investment and spending, including wide-spread development of rail networks in the western regions of Europe (Farhadi, 2015). Between 1888 and 1920, transport infrastructure was negatively associated with house prices, a finding that can be linked to the lead up to World War I and the period of the war itself where investments slowed down. Starting from 1920, the effect of transport infrastructure remained relatively flat for most of the period except for some minor surges. For instance, there was a minor surge between 1965 and 1980 where the positive effect of transport infrastructure on house prices was slightly more pronounced. This period coincides with the 'golden age' of economic expansion when most nations enhanced investment expenditures towards the post-war reconstruction and recovery (Madsen, 2008). The relatively flat effect of transport infrastructure is also likely to reflect the law of diminishing marginal returns to transport infrastructure investments. Thus, following investments as part of post-war reconstruction efforts, transport infrastructure development is expected to reach a peak point where further drastic effects on house prices are unlikely.

From Fig. 4, among the control variables, we find that the estimate of GDP per capita is very non-linear characterised by positive effects and

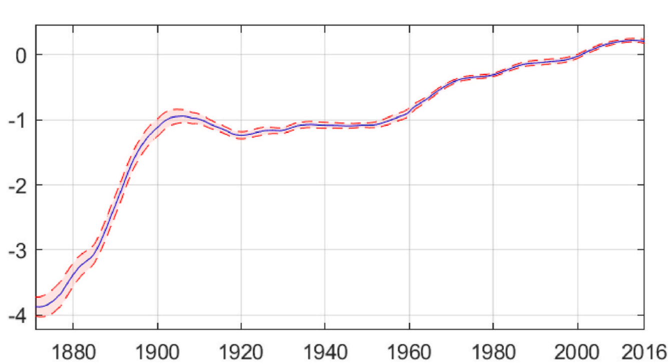

Fig. 2. Non-parametric estimate: common trend.

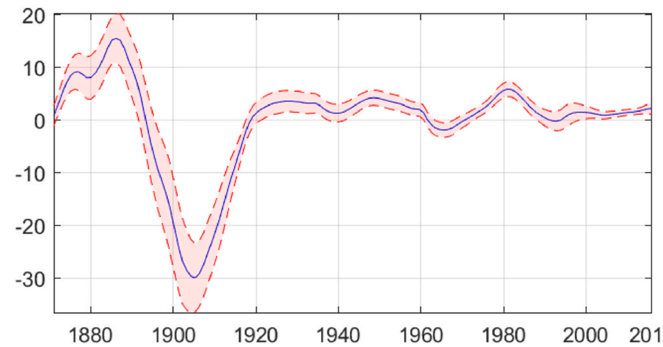

Fig. 3. Non-parametric estimate: infrastructure stock.

insignificant effects for an extended period. Specifically, we find mostly positive effects of GDP per capita until around 1888 when the estimates are statistically insignificant before becoming significant (positive) again between 1943 and 1960. The estimates remain insignificant after that with significant positive effects after 2010. The effect of population is positive and statistically significant across the years, except for a sustained period of a negative effect between 1882 and 1900. The effect of mortgage loans to GDP ratio is non-linear, with evidence of a sustained positive effect for the entire sample period except for negative effects between 1888 and 1910. The estimates on non-mortgage loans to GDP ratio are mostly positive for the sample period. The effect of interest rate is negative until 1900 and remains positive for the rest of the period except for statistically insignificant effects between 1920 and 1960. The estimates of the inflation rate are relatively flat across the sample period with negative estimates between 1988 and 1905.

Fig. 5 plots the common and individual trend estimates. In each of the graphs, the 95% confidence intervals are represented by the dotted red lines. The solid dark-blue lines represent the common trend, while the country-specific trend is plotted in a black dashed line accompanied by plots of actual house prices series in light blue. Except for some minor differences across countries, the country-specific trends are generally consistent with their common trend component. For countries such as Belgium, Denmark, Spain, Netherlands, Norway, Sweden, and the US, we observe that the country-specific trends are persistently above the common trend. In Portugal, the opposite is observed. This is also the case for Japan, which reflects long periods of stagnation until the mid-20th century, with a relatively short boom in real house prices occurring between 1949 to the 1980s (Knoll et al., 2017).

4.4. *Channels of influence*

Discussions in Section 2 suggest that economic growth, employment, and crime are potential channels through which transport infrastructure influences house prices. Specifically, transport infrastructure is positively associated with economic growth and employment, which are, in turn, positively associated with house prices. In contrast, transport infrastructure has been found to facilitate crime, which is known to depress house prices (Hailemariam et al., 2021). That our results show a positive effect of transport infrastructure on house prices is an indication that the dominant channel(s) at work in the context of our study is economic growth or employment. We take advantage of data available for employment and robberies, which we use as a proxy for crime, to examine the role of all three variables as potential mediators in a system of structural equation. Employment is measured using economy-wide employment data drawn from Madsen et al. (2018) and is available only from 1870 to 2011. To capture crime, we construct a new dataset consisting of robberies per 100,000 people dating from 1900. Data on robberies for all 17 OECD countries from 1900 to 1974 are taken from Archer and Gartner (1987) and updated using data from Von Hofer et al. (2012), the UK Government Statistics Office, the US Department of

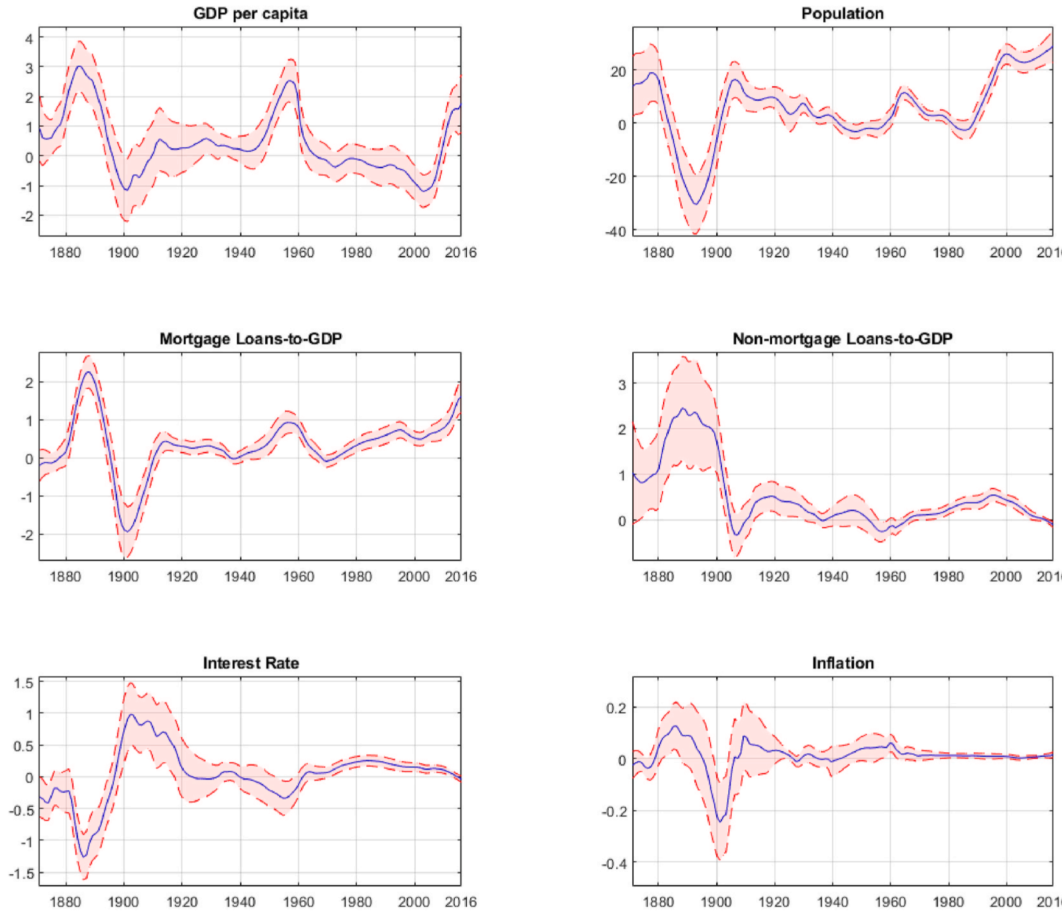

Fig. 4. Non-parametric estimate: covariates.

Justice UCR Database, and the Global Economy Database.[7]

We conduct a multiple mediation analysis using a structural equation model (SEM) to estimate the potential role of employment, economic growth, and robberies as mediators in the relationship between transport infrastructure and house prices, and to determine how much of the indirect relationship between these two variables, if any, is channelled through these potential mediators.

First, given that employment data is available from 1870 to 2011 and robberies data is available only from 1900, the inclusion of both variables in regressions from Table 3 will limit the analysis to observations from 1900 to 2011. Before reporting SEM results, we re-estimate our model with the restricted sample for the period 1900 to 2011 to examine the sensitivity of our results to this sample as well as examine the effects of our mediators on house prices. These results reported in Table 5 show that our results remain robust to the changes in the sample as well as the inclusion of employment and robberies as additional covariates. We also find that the coefficient on GDP per capita remains positive, and thus, economic development is positively associated with house prices. However, employment is negatively associated with house prices, while the coefficient on robberies is statistically insignificant.

SEM results are presented in Table 6. We find that an increase in transport infrastructure stock is associated with an increase in economic growth. The effect of transport infrastructure on employment and robberies is, however, statistically insignificant. Thus, the data does not support employment and robberies as channels through which transport infrastructure influences house prices. The results, however, show that the total indirect effect of transport infrastructure on house prices through the significant channel (i.e., economic growth) is statistically significant with an effect size that is approximately 25% of the total effect of transport infrastructure. Our results thus confirm economic growth as a channel through which transport infrastructure influences house prices.

5. Conclusion

Transport infrastructure stock has increased significantly since the eighteenth century in what has been called the transport revolution. This has inspired a growing body of literature that examines the relationship between transport infrastructure and other factors. At the same time, house prices have also experienced a sustained increase, particularly in the past few decades. Is there a relationship between transport infrastructure and house prices? Like some previous studies, we examined this research question but took a unique approach that differs from the existing literature. Unlike previous studies that often examine this question using case studies of single cities or countries and study the relationship over a short timeframe, we used a sample of high-income OECD countries, most of which substantially invested in transport infrastructure since the eighteenth century. Specifically, we examined the relationship between transport infrastructure and house prices using panel data from 17 OECD countries over the period 1870 to 2016. In doing so, we show how the evolution of transport infrastructure since the nineteenth century influenced house prices. We estimated parametric models that account for interactive fixed effects, as well as non-parametric models that account for complex non-linearities and the

[7] For the UK, see, https://www.gov.uk/government/statistics/historical-crime-data; for the US, see https://www.ucrdatatool.gov/Search/Crime/State/RunCrimeStatebyState.cfm; for the Global Economy Database, see https://www.theglobaleconomy.com/download-data.php.

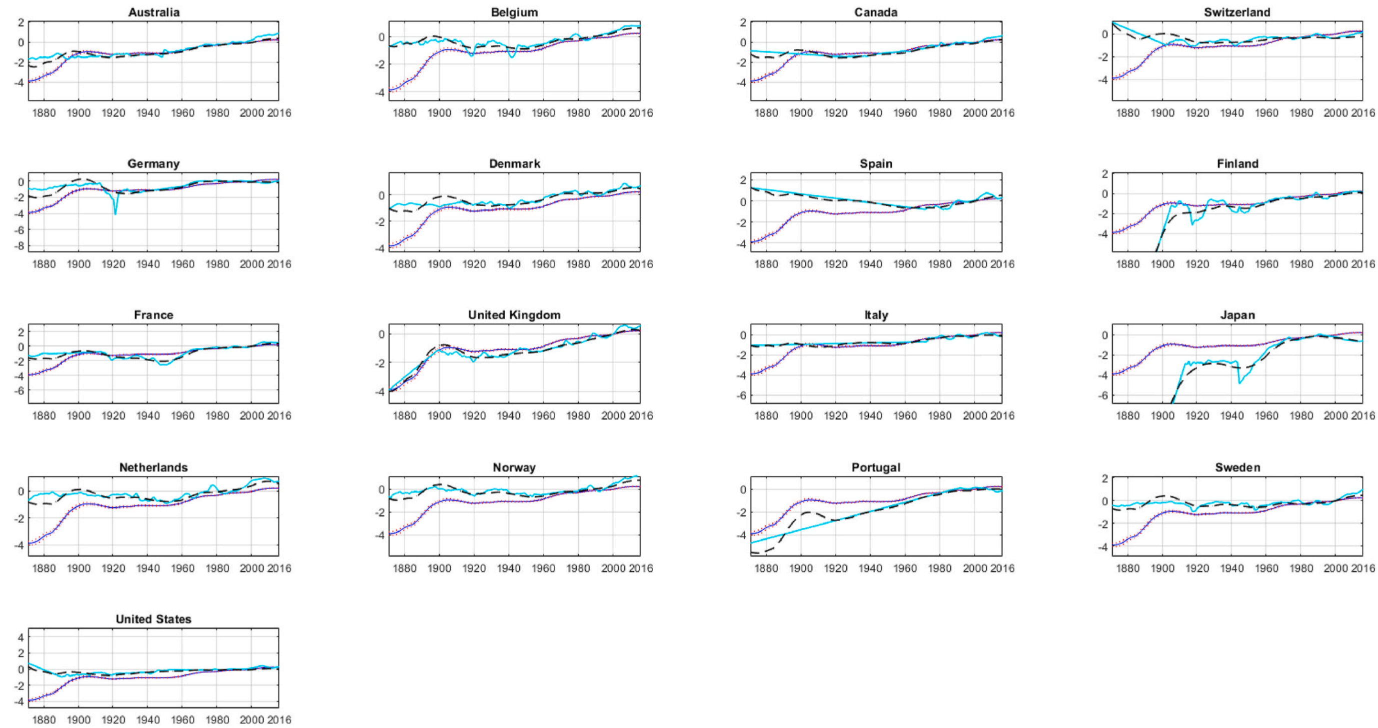

Fig. 5. Non-parametric estimate: country-specific trend.

Table 5
Sub-sample analysis (1900–2011).

	Dependent variable: real house prices	
	(1)	(2)
INFR	0.035**	0.051**
	(0.006)	(0.006)
	[0.024, 0.047]	[0.039, 0.062]
GDP	0.210**	0.214**
	(0.015)	(0.015)
	[0.179, 0.237]	[0.181, 0.239]
POP	−0.084**	−0.067**
	(0.009)	(0.009)
	[-0.100, −0.066]	[-0.081, −0.047]
ML	0.137**	0.118**
	(0.013)	(0.013)
	[0.113, 0.164]	[0.096, 0.148]
NML	0.225**	0.207**
	−0.02	(0.020)
	[0.184, 0.262]	[0.162, 0.243]
IR	−0.297**	−0.273**
	(0.026)	(0.026)
	[-0.345, −0.245]	[-0.321, −0.221]
INFL	0.070**	0.064**
	(0.006)	(0.007)
	[0.057, 0.082]	[0.052, 0.077]
EMP		−0.187**
		(0.033)
		[-0.252, −0.128]
ROB		0.004
		(0.004)
		[-0.003, 0.012]
Interactive FE	Yes	Yes
Observations	1904	1904

Columns (1) report results for regressions that exclude employment and robberies.
Columns (2) report results for regressions that include employment and robberies.
Notes: Numbers in parentheses and brackets are standard errors and 95 per cent confidence intervals based on 999 replications using wild bootstrap. ** indicates statistical significance at the 5 per cent level.

Table 6
Multiple mediation analysis.

	Effects of INFR
Mediating variables	
GDP	0.295***
	(0.019)
EMP	−0.002
	(0.017)
ROB	0.315
	(0.638)
Total indirect effect	0.066***
	(0.022)
Direct effect	0.197***
	(0.029)
Combined effect (total indirect effect + direct effect)	0.263***
	(0.026)
Observations	1904

Notes: Standard errors in parentheses. *** indicates statistical significance at the 1 per cent level.

time-varying relationship between the two variables.

Our main conclusion is that transport infrastructure has a positive direct effect on house prices. This conclusion is robust to multiple sensitivity checks. Our non-parametric models confirm this average positive relationship and suggest that this relationship has varied significantly over time and in response to historical events. In exploring the channels through which this positive relationship is transmitted, we find that transport infrastructure influences house prices through the channel of economic growth. We find no empirical evidence for the earlier discussion that employment growth and crime rates are also channels of transmission.

These findings have significant policy implications at both the macro and micro levels. They suggest that transport infrastructure investments will accompany house price growth. With the sustained rise in house prices, as well as deepening income inequality associated with it, these findings lend guidance to policy decisions at the micro-level (i.e., local council or urban planning levels). At the macro or country level, our finding that transport infrastructure influences aggregate house prices via economic growth, lends support to the need for infrastructure development as a way to promote economic growth. The positive effect of transport infrastructure on economic growth suggests that policies aimed at promoting nationwide infrastructure development can help promote economic growth and promote equality. More generally, development of transport infrastructure can promote different sectors at the macro-level. For instance, through transport infrastructure investments, countries can create new markets, promote trade, and encourage inter-country integration as observed across Europe. Inter-country accessibility, mobility and trade rely on effective transport networks, and our findings show that these ultimately promote house prices. Thus, policymakers seeking to bridge the economic development gap at the country level can focus on investing in transport infrastructure that enhances connectivity with neighbouring countries, as observed in the European Union, to achieve the required level of growth.

As transport infrastructure investments continue to evolve, this study shows that house prices will be directly and indirectly influenced, the latter being transmitted specifically through economic growth. Future research can explore the evolving dynamics in relation to the several mechanisms through which transport infrastructure transmits to house prices, some of which are discussed in this study but not empirically examined due to data limitations. Importantly, different forms of transport infrastructure are likely to influence house prices differently. For instance, airport infrastructure and road infrastructure are likely to impart house prices differently, and via different channels. However, given that our transport infrastructure variable is a composite indicator that captures the different dimension of transport, we are not able to unravel the different effects in this study. Future studies can focus on better understanding the impact of different transport infrastructures on house prices and the relevant channels through which they work.

Authors' contribution

SAC: study conception and design, analysis and interpretation of results, manuscript writing, manuscript review. KTB: resources, manuscript writing, manuscript review. KM: resources, manuscript writing, manuscript review. QD: data collection, analysis and interpretation of results, manuscript writing, manuscript review.

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