Songlines*

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Abstract

This paper examines the long-term economic impacts of the adoption of local knowledge during European colonisation. We use the case of Australia, where Aboriginal knowledge of the landscape was integral to colonial exploration and settlement. To quantify the effects of this knowledge, we construct a newly digitised and georeferenced dataset of trade routes created by Aboriginal people based on oral traditions, known as *Songlines*. Our results indicate that Aboriginal trade routes are strongly associated with current economic activity as measured by nighttime satellite imagery and, alternatively, population density. We attribute this association to path dependence and agglomeration effects that emanate from the transport infrastructure built by Europeans roughly along these routes, which have agglomerated economic activity. Finally, by exploiting exogenous variation in optimal travel routes, we provide evidence that our results are not entirely determined by the inherent characteristics of Australian topography, but rather by Aboriginal knowledge.

Keywords: Aboriginal trade routes; Songlines; colonialism; agglomeration; Australia
JEL Codes: N77; O10; R12; Z10; Z13

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1. Introduction

The economic legacy of European colonisation has been a subject of considerable scholarly interest (Sokoloff and Engerman, 2000; Acemoglu et al., 2001; Acemoglu et al., 2002; Glaeser et al., 2004; and Dell, 2010). A central focus of this research is to understand the drivers behind the patterns of European settlement and their long-term economic consequences (Easterly and Levine, 2016). To explain these patterns, scholars have traditionally relied on the hypothesis of first-nature geography, according to which the natural features of the landscape played a decisive role (Sokoloff and Engerman, 2000; Acemoglu et al., 2001). However, a less explored dimension in the literature is the role of second-nature geography, i.e. activity associated with the local knowledge possessed by the Indigenous population, in shaping European colonisation and its aftermath (Caruana-Galizia et al., 2021).

There are numerous examples outside of economics that illustrate how the adoption of local knowledge shaped European colonial expansion. A notable example is Plymouth Colony, the second English colony in the United States, founded by Pilgrims in 1620. Historians have documented that the use of native knowledge of corn cultivation enabled settlers to survive the first years of colonisation, ultimately ensuring the continuity of the colony and contributing to the expansion of European colonisation (Mann, 2005).[1] Despite the fact that anthropologists and historians have widely recognised this important channel, the economics literature has yet not fully investigated its potential economic impacts. Moreover, the underlying mechanisms that explain the path-dependence of these economic effects remain unexplored. We aim to fill this gap by focusing on Australia where the adoption of Aboriginal knowledge of the landscape was an integral part of colonial exploration and settlement:

"*The natives were the parties who first guided the White Man through the intricacies of their forests, led them to their Rivers, their springs, and rich pastures, assisted them in keeping their stock, watched their working oxen, tracked their stray Horses, and rendered other essential assistance . . . The knowledge of their Country was thus acquired, was turned to account*"(Reynolds, 1980).

By the time of contact with Europeans in the early seventeenth century, Aboriginal people in Australia had developed an extensive trading network based on oral traditions (Flood, 1983; Veth and O'Connor, 2013; Kerwin, 2010; McBryde, 2000). This oral tradition is known as *Songlines*, which contains information about the land and how Aboriginal people had to travel to their various destinations (Chatwin, 1987;

[1] For a recent overview of why colonisation is considered an important factor explaining the origins of modern economic growth, see Koyama and Rubin (2022).

Norris and Harney, 2014). Anthropologists refer to this network as "multitudinous", extending across Australia in all directions (Mountford, 1976; Kerwin, 2010, p. 63). Recent anthropological evidence indicates that this trading network provided Europeans with vital knowledge for exploring and settling mainland Australia during colonisation. For instance, Kerwin (2010) noted that "*European exploration of Australia...was made possible by Aboriginal trading paths...Surveyors quickly expanded European occupation and territories, and they coloured the map of Australia in their image*". Importantly, while this adoption of knowledge was thought to have been ephemeral, we argue that it had a profound and longlasting impact on the evolution of modern economic activity and urbanisation patterns in Australia. Upon settlement, Europeans created transport networks to connect the main colonies, which led to improved connectivity and an increase in economic activity roughly along these routes.

We test empirically our main hypotheses by creating a new dataset on Aboriginal trade routes. We do so by collecting anthropological data on Aboriginal trading sites published in a series of research articles by Frederick David McCarthy (1939). These publications provided one of the most comprehensive qualitative descriptions of all known points of origin and destination associated with Aboriginal people prior to colonisation. We gain systematic information about these sites through careful reading and compilation. This yields a catalogue of 1,026 origins and destinations spanning mainland Australia.

Armed with the above unique data, we develop a novel georeferenced map of Aboriginal trade routes in Australia. To construct the network, we employ a least cost path algorithm to identify optimal routes between the 1,026 origins and destinations. Our approach is based on the hypothesis that Aboriginal people selected paths based on their biological constraints and environmental conditions as indicated by anthropological research (Kerwin, 2010). The algorithm uses the Human Mobility Index (HMI) developed by Özak (2018). The HMI estimates the time it took people to move around a square kilometre of land in pre-industrial times, taking into account temperature, relative humidity, cloud cover, slope, type of terrain and risk of heat exhaustion. We find that 513 distinct trade routes comprise the entire network with results consistent with the non-georeferenced maps of McCarthy (1939).[2]

We then document the long-term effects of Aboriginal trade routes on contemporary economic activity in Australia. To this end, we divide Australia into 10 km x 10 km grid cells and use nighttime satellite den-

[2] As well as providing detailed anthropological descriptions of the different origins and destinations where Aboriginal people traded, McCarthy (1939) also produced a series of maps illustrating some of the Aboriginal trade routes. We use these maps as an alternative source, but as we will point out, these maps do not appear to show the entire network of Aboriginal trade routes, only the most representative routes.

sity as a proxy measure for economic activity.[3]We also consider population density as an alternative outcome.[4,5] Utilising local government fixed effects to control for unobserved, government-specific characteristics, we find a positive and statistically significant association between Aboriginal trade routes and current economic activity. Specifically, we find that the presence of an Aboriginal trade route increases the probability of observing economic activity in contemporary Australia by 3%.

It is particularly important to determine whether the spatial features of Australia's economy have been shaped by first-nature geography, that is by the landscape, or by the second-nature influence of Aboriginal trade routes. In our estimation models we control for a range of geographic and climatic features so as to mitigate potential confounding factors. In addition, we examine historical mining activities as a possible explanation for rapid urbanisation during the colonial 'gold rush' in Australia. We find that, even after controlling for these factors, our empirical analysis continues to demonstrate a positive and statistically significant correlation between Aboriginal trade routes and contemporary economic activity.

To ensure the robustness of our main results, we conduct a rigorous examination of various factors that could potentially affect them. In particular, we find that geographical variation, unobserved characteristics of neighbouring cells, measurement error in the reconstruction of Aboriginal trade routes, spatial autocorrelation and omitted variable problems have no impact on our results.

To delve into the effects of Aboriginal trade routes on the emergence of new settlements in Australia, we utilise data on the year of foundation for 249 major cities between 1788 and 2000 (Kampanelis, 2019). Our results indicate that these trade routes are predictive of new settlements up to 1900, with early settlements typically founded near to an Aboriginal route. These findings provide support for our interpretation that Europeans used Aboriginal knowledge of the landscape to establish their earliest settlements.

Next, we focus on the mechanisms that can explain our main results. We hypothesise that the influence of Aboriginal trade routes can be partially attributed to path dependence and associated agglomeration effects resulting from the operation of early European transport infrastructure. Specifically, when Europeans settled in new areas,

[3] In particular, we use the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. Relative to the alternative source from the Defence Meteorological Satellite Programme (DMSP), VIIRS has 45 times smaller pixel footprints, thus improving data accuracy in rural and desert regions, which are especially pertinent to our case study.

[4] We thank Andrew Foster and Edward Glaeser for insisting that we also use population density as an outcome.

[5] We measure population density as the logarithm of the number of persons per grid cell, drawn from the Global Human Settlement Layer (GHSL).

they built transport networks connecting these settlements to major colonies (Kerwin, 2010). This likely caused these routes to become increasingly associated with economic activity as a result of increased connectivity over time. To quantitatively investigate this mechanism, we digitise and georeference a series of maps showing the 19th and 20th century Australian railway and road networks. We find a strong positive relationship between Aboriginal trade routes and early transport infrastructure. Our findings are consistent with an existing body of literature analysing the impact of historical trade routes on contemporary outcomes (Dalgaard et al., 2018; Flückiger et al., 2021). These studies argue that regions with earlier investments in transport infrastructure tend to have higher levels of connectivity over time due to lower transportation costs and further investments in infrastructure.

Finally, we proceed to validate the plausibility of our identification assumption. Our main argument is that the adoption of Aboriginal knowledge of the landscape influenced the way Europeans explored and settled Australia, and thus decisively shaped the spatial distribution of modern economic activity. An important caveat to our empirical findings, however, is whether they actually reflect an adoption of Aboriginal knowledge and are not due to the inherent characteristics of Australian topography. If the latter is the case, it is conceivable that in their exploration of Australia, Europeans preferred places with other favourable environmental features and deviated from Aboriginal routes, i.e. perhaps because some Aboriginal groups cooperated less with Europeans, or because they evaluated the suitability of the landscape differently. This would mean that Australia's spatial development would have followed different geographical patterns. To confirm our identification, we leverage exogenous variation in European exploration and settlement of Australia. Building on recent research by Barjamovic et al. (2019), we construct Natural Routes in Australia that include geographically suitable routes from each coastal cell to the interior. These routes shed light on the most traversable routes that Europeans might have used when exploring Australia on their own.

We first examine the predictive power of both Natural Routes and Aboriginal trade routes with respect to European exploration of Australia. To this end, we create a measure of European exploration by digitising a map covering all early European inland expeditions from 1606 to 1901. In a "horse race" analysis, our results show that the coefficient for Aboriginal trade routes has three times the predictive power in determining the extent of European exploration in Australia than the estimate for Natural Routes, which has only marginal statistical significance. We then examine which of these two variables exerted an influence on patterns of European settlement and modern economic activity. Surprisingly, our empirical results show no relationship between Natural Routes and the establishment of new settlements in Australia, nor with historical railways, while the Aboriginal trade routes measure remains statistically significant. Finally, we show that while Natural Routes can predict nighttime light density, the presence of modern roads, and population density in Australia, their effect is only half as large as that estimated from Aboriginal trade routes, especially on the former. This result strongly suggests that the process of modern urbanisation and economic activity in Australia is deeply rooted in Aboriginal knowledge adopted by Europeans during colonisation.

Our research contributes to several strands of literature. There is a well-established line of studies that highlight the enduring economic consequences of colonisation (Sokoloff and Engerman, 2000; Acemoglu et al., 2001; Acemoglu et al., 2002; Glaeser et al., 2004; Acemoglu and Johnson, 2005; Dell, 2010; Bruhn and Gallego, 2012; Kampanelis, 2019). However, the influence of local knowledge during colonisation has been understudied, despite the fact that it was a common practise of Europeans to use it for colonial expansion. Using the case of Australia, we provide the first quantitative evidence of the extent to which the adoption of local knowledge by colonisers shaped European settlement and, consequently, long-term development. In particular, we document that Europeans appear to have been aided by Aboriginal people for exploration and settlement during colonisation by following a unique network of trade routes. We demonstrate that this specific historical event had an important impact on the emergence of early settlements in Australia, which continues to influence economic activity today.

Our research also contributes to the literature on the determinants of urban development and its spatial aspects, including their agglomeration effects (Glaeser et al., 1992; Page, 1999; Bosker et al., 2013; Duranton and Puga, 2014; Bleakley and Lin, 2015; Bosker and Buringh, 2017; Barsanetti, 2021). Of particular relevance is the study by Barsanetti (2021), which examines the impact of the pre-colonial Peaubiru path on the emergence of modern cities in a small region of Brazil. Barsanetti finds that areas closer to the Peaubiru path had higher population density and urbanisation. However, due to its local-specific focus, the study is limited in drawing broader conclusions about the long-term impact of pre-colonial trails, covering only a few areas in two Brazilian states, São Paulo and Paraná.

Our work is the first comprehensive study to investigate the impact of pre-colonial trade routes across an entire continent, incorporating the entire universe of Indigenous trade routes. Similarly to Barsanetti (2021), we find strong evidence of economic activity concentration in areas where pre-colonial trade routes existed in Australia. Unlike Barsanetti (2021), we also uncover that modern transport networks, including roads, are closely associated with Aboriginal trade routes.

Additionally, we provide evidence of the dynamic effects of Aboriginal trade routes, demonstrating their influence mainly on the emergence of cities in early European settlements.

Our findings also contribute to recent studies that have documented the role of pre-colonial factors in shaping contemporary outcomes. Gennaioli and Rainer (2007), Michalopoulos and Papaioannou (2013), Arias and Girod (2011), Angeles and Elizalde (2017), and Elizalde (2020) have documented the role of pre-colonial institutions in shaping contemporary economic outcomes in Africa and Latin America. Dincecco et al. (2020) examine the long-term impact of pre-colonial wars on contemporary development in India. This paper contributes to this literature by showing that pre-colonial factors may still matter even for countries that emerged as "winners" from the colonisation process and where societal heterogeneity was limited.

This paper also contributes to the growing literature on the long-term impact of historical trade routes by departing from prior studies that focus on societies where transport infrastructure projects were implemented by centralised states (Wahl, 2017; Dalgaard et al., 2018; Barjamovic et al., 2019; De Benedictis et al., 2018; Michalopoulos et al., 2018; Garcia-López et al., 2015; De Benedictis et al., 2018; Flückiger et al., 2021; Baniya et al., 2020; Ahmad and Chicoine, 2021). We shift our focus to societies in which economic interactions were paramount even when there was a lack of state or physical infrastructure. Specifically, we argue that Aboriginal trade routes in Australia facilitated the development of modern urbanisation.

Finally, our study contributes to the growing literature examining the long-term effects of historical events on current outcomes. Nunn (2008) finds that Africa's underdevelopment is rooted in the African slave trade between the 15th and 20th centuries. Similarly, Valencia Caicedo (2019) reveals that religious missions among Indigenous Guarini, who settled in South America between 17th and 18th centuries, have resulted in higher educational attainment today. Additionally, Lowes and Montero (2021) argue that due to colonial medical campaigns in French Equatorial Africa, areas with such a history have less trust in Western health interventions today. Our results show that while the adoption of Aboriginal knowledge by colonisers was temporary, it appears to have determined the patterns of European settlement during colonisation in Australia, which in turn affected significantly the geographical contours of urbanisation and economic activity today.

The remainder of the paper proceeds as follows. Section 2 outlines a brief background on Aboriginal people, Aboriginal trade routes and European colonisation in Australia. Section 3 describes the data and presents the main empirical results and robustness checks. Section 4 explores the dynamic effects of Aboriginal trade routes. Section 5 focuses on mechanisms. Section 6 validates the identification assumption. Section 7 concludes. An extensive set of additional details backing up our analysis is given in the Appendix.

2. Background

The first human immigration to Australia is estimated to have occurred some 40,000 years ago. Flood (1983, p. 77) provides anthropological evidence that suggests the first migrants, hereafter referred to as Aboriginal people, arrived via the Southeast Asian islands and settled the Kimberley region of Western Australia. Subsequent migration patterns indicate that between 1,350 and 2,200 years passed before Aboriginal people had settled the entire continent, traveling both inland and along the coastal regions (Ibid, pp. 77-80). This event marked the human settlement of the third (of four) habitable continents in the world, following Africa and Eurasia (the latter comprising Europe and Asia).

Despite its early settlement, Aboriginal people never developed hierarchies that surpassed the band level, as stated by Diamond (2013, p. 44): "*Australia is the sole continent where in modern times all native peoples still lived without any of the hallmarks of so-called civilisation... Aborigines were nomadic or seminomadic hunter-gatherers organized into bands*".

Aboriginal people lacked the domestication of animals, which may explain why they remained hunter-gatherers until the 17th century when Europeans began colonising Australia. This limitation was due to the Australian megafauna dying out shortly after the arrival of Aboriginal people (Veth and O'Connor, 2013). Indeed, without the domestication of animals, Aboriginal people were unable to increase food production and develop denser societies, which were prerequisites for more complex political hierarchies (Diamond, 2013, pp. 81-88).

In Australia, domestication and cultivation of plants was also limited by infertile soils, unpredictable climate and narrower (relative to Eurasia) East-West span of climatic variation. These hindered the transition from hunter-gatherer societies to agricultural societies (Diamond, 2013, pp. 296-297). This led to a limited availability of food resources and a low population density: it is estimated that at the time of contact with Europeans, there were approximately 300,000 Aboriginal people in Australia (Kerwin, 2010, p. 63).

Nevertheless, Aboriginal people developed relatively advanced ancient features such as extensive trade routes. Veth and O'Connor (2013) report that the exchange of ochre pigments can be traced back to 30,050 BC, with some traded across distances of 125 to 500 kilometres. Subsequent trade routes extended even further. Flood (1983, pp. 247) documents how shell jewellery from the Dampier Peninsula in north-western Australia was traded as far as the south coast of the continent, a distance of 1,600 kilometres. Anthropologists describe the Aboriginal trade network as "multitudinous", extending in all directions across Australia (Mountford, 1976; Kerwin, 2010, p. 63). According to McBryde (2000), "*Australia is overlain by a matrix of [Aboriginal trade routes], often continent-wide, binding individuals and societies*".

Aboriginal people developed complex trade routes to compensate for the poor quality of Australian soils. Specifically, Aboriginal people had to frequently travel long distances in search of sustenance. This nomadic lifestyle facilitated exchanges of goods between neighbouring groups and enabled the acquisition of valuable knowledge about the landscape. Anthropologists have documented that Aboriginal trade routes connected various water sources such as wells and springs (Reynolds, 1990). Early accounts by European explorers attest to the Aboriginal people's comprehensive understanding of the landscape: "*The localities selected by Europeans ... are those that would be equally valued...by the natives themselves ... as places ... which they could most easily procure food*" (ibid., p. 17).

Since Aboriginal people did not have a written language, they developed an extensive system of oral traditions, often referred to as *Songlines*, to pass on knowledge of the landscape to subsequent generations. European explorers noted the utility of these paths, which cross-connected trade routes and guided them to critical water sources (Kerwin, 2010, p. 138). Studies have shown that these oral maps were also used to map out trade routes due to Aboriginal peoples' profound knowledge of the sky, which has been documented in various Aboriginal stories (Cairns and Harney, 2004; Norris and Harney, 2014). Wositsky and Harney (1999) define *Songlines* as "*epic creation songs passed to present generations by a line of singers...[which] provide maps for the country," and some of these "describe a path crossing the entire Australian continent.*"[6]

The Two Dog Dreaming is an example of a long-distance trade route connected by Aboriginal *Songlines*. This route, estimated at approximately 3,800 km, surpasses in scope and history ancient routes such as the Silk Road, the Incense Road, and the Inca Road (Kerwin, 2010, p. 89). Pituri, a stimulant leaf chewed or smoked before Europeans introduced tobacco, was traded along this route. Part of this network of *Songlines* is located along the Transcontinental Railway in Australia, which was completed in 1917 and connects eastern and western Australia over a distance of 1,693 km.

Kerwin (2010, p.89) identified the Pituri trade route as an example

[6]This is reminiscent of the prevailing theory of how the Homeric epics were passed down from generation to generation by "singers of tales", who performed from memory, over hundreds of years until the epics were written down in the sixth century BCE (the so-called Pisistratean Recension) (Lord, 1960). The *Songlines* were popularised by Chatwin (1987).

of an Aboriginal trade route, which connected six trading centres from Marree in the south to Dajarra and Urandangi in the north, spanning a distance of 1,200 km.[7] Queensland was a particularly prominent region in which these trade centres were located.

European settlement of Australia began in the early 17th century with explorations that led to the establishment of the first British colony at Sydney Cove in 1788. This was soon followed by a push to open up more land for agricultural production. In the early 1810s, expeditions were organised to cross the Blue Mountains, a large mountainous region bordering Sydney. Ultimately, this endeavour led to the discovery of Bathurst by the explorer George Evans, which became the first inland settlement in Australia.

The European expeditions were successful, largely due to the adoption of Aboriginal knowledge of the landscape. Reynolds (1980) reveals that Aboriginal people were instrumental in aiding European expeditions, providing them with crucial information about routes, as well as practical skills to sustain their navigation of the harsh environment. Not only did Aboriginal people provided explorers with invaluable knowledge of fords, passes, short-cuts and easy gradients, they also taught them how to obtain clean water and a variety of food sources, ranging from hunting and fishing to bush tucker. This adoption of knowledge was essential to the success of European expeditions.

There is clear anecdotal evidence that Aboriginal knowledge of the landscape enabled Europeans to establish early settlements in Australia. Reynolds (2006) and Kerwin (2010) present excellent accounts of the relationship between European explorers and Aboriginal people, while Henrich (2015) provides an interesting account of the reliance on local Aboriginal knowledge to make early European expeditions more successful. One influential colonial officer stated, "*The natives were the parties who first guided the White Man through the intricacies of their forests, led them to their Rivers, their springs, and rich pastures, assisted them in keeping their stock, watched their working oxen, tracked their stray Horses, and rendered other essential assistance... The knowledge of their Country was thus acquired was turned to account*" (Reynolds, 1980). This suggests that Aboriginal knowledge of the landscape was essential for the establishment of early European settlements in Australia.

It is interesting to consider now how the adoption of Aboriginal knowledge of the landscape may have impacted the long-term development of the country. While it is true that the adoption aided Europeans in locating suitable settlements, this became less necessary once these settlements were established, mapped, and connected to

[7] The trading centres that dot the Pituri track are Marree, Birdsville, Bedourie, Boulia, Dajarra and Urandangi.

the main colonies. Yet, it is plausible that the influence of Aboriginal trade routes, which linked early settlements to the major colonies via transport infrastructure, endured even after Europeans no longer required them to travel between settlements.

Following the European expeditions that opened up new areas for permanent settlements, construction of transport infrastructures emerged as a necessary tool for connecting these regions. For example, shortly after the discovery of the Bathurst Plain by explorer George Evans, a road was built to connect it with the main colonies and ports in Australia (Herald, 1912 [Online]). Anthropological research has also highlighted numerous instances of railway lines and roads that ran along Aboriginal trade routes (Kerwin, 2010). A noteworthy example is the Transcontinental Railway, which joined the major colonies in eastern and western Australia in the early 1910s, and was based on the Dog-Dreaming Trails mapped by John Forrest and others in the 1870s (Reynolds, 1980).[8]

3. Data and Empirical Results

Our data construction and selection of variables is aimed at measuring all aspects of Australian urbanisation. We place particular emphasis on the Aboriginal trade routes as well as counterfactual proxy routes that are defined so as to let us examine both first- as well as second-nature geography and topography of Australia and perform several robustness checks. We present our results starting in section 3.4, followed by robustness checks and related analyses in section 3.5. Section 6 aims at establishing the plausibility of our identification strategy. Section 7 concludes.

3.1. Construction of Variables of Interest

The variables of interest in this study consist of all Aboriginal trade routes along the Australian land. Each route is defined by an origin and a destination, obtained from the trilogy of research articles on Aboriginal trade routes by the anthropologist and archaeologist Frederick David McCarthy (1939). Prior to analysing the construction of the Aboriginal trade route dataset, it is essential to provide a brief overview of the anthropological source utilised.

McCarthy (1939) used similar techniques to those employed more recently by other anthropologists in constructing datasets that measure pre-colonial characteristics of ethnic groups, such as Murdock (1967). Specifically, McCarthy utilised early written accounts from the time of

[8]Forrest's writings on Aboriginal knowledge of the landscape have been widely referenced in the literature on European exploration of Australia (Reynolds, 1980).

contact with natives to inform his dataset.[9] We manually obtained this information from the accounts by identifying the origin and destination of each Aboriginal trade route on the Australian mainland. Two such examples are provided below, demonstrating the trade of red ochre[10] and pituri, respectively, between South Australia and the Northern Territory:

Example 1: *"Jessop...says that at "these three places, Noarlunga, Augusta and Aroona, situated at distances of 150 miles in a direct line from south to north, where they interchanged their respective earths or clays, the natives drove also a good trade in skins with those who lined further inland""*.

Example 2: *"Johnston and Cleland... state that " it is probable that the supply of pituri of the Ooldea area is secured from the Musgrave and Everard Ranges... along the recognized and known trade routes between these areas... there is a native trade route passing more or less north-east from Alice Springs via Aritunga, Ambalindum, the Plenty, MacDonald Downs, The Sandover, thence via the native wells to the Georgina at Lake Nash""*.

We geocoded each origin and destination by means of their corresponding longitude and latitude. This generated a set of 1,026 origins and destinations, encompassing all Australian states (except Tasmania). Consequently, the primary variables of interest consist of 513 Aboriginal trade routes. The set of 513 routes connecting 1,026 origins and destinations is a small number compared to the universe of all possible connections $(513 \times 512/2)$, suggesting that Aboriginal people did optimise with respect to all possibilities. We return to this issue in section 6 below.

Drawing the lines between all origins and destinations requires taking into account climatic, environmental, and physiological constraints on people. Specifically, Aboriginal people, having travelled across the entirety of Australia for thousands of years, must have been able to select travel routes whose environmental and climatic conditions suited them best, considering their biological constraints and food and water conservation technologies.

Therefore, we employ the Human Mobility Index (HMI), due to Özak (2018), to guess the most cost-effective route between each pair of origin and destination points via a least-cost path (LCP).[11] Other than the

[9] For example, Peter Beveridge, a British colonist, spent twenty three years (1845 to 1968) documenting Aboriginal practises, including trade, among various tribes on the Lower Murray River, now Sawn Hill.

[10] Red ochre is a pigment used by Aboriginal people for ceremonies, rock art, and to decorate various objects.

[11] Since the HMI raster file lacks data on the initial layer of coastal grid cells in Australia, we were unable to employ the least-cost path algorithm for establishing Aboriginal trade routes. As a result, we have excluded these particular grid cells from our analysis. But even if we had created

information provided by the maps and sketches in McCarthy (1939), we do not know those exactly.[12] Importantly, this index gives the travel time on each square kilometre of land in pre-industrial times, taking into account temperature, relative humidity, cloud cover, slope, type of terrain (e.g. natural trails or loose sand), and risk of heat exhaustion, which refers to the effects of heat on an individual's metabolic rate and speed to avoid exhaustion. Thus, the HMI is an estimate of the time it takes a person to traverse each square kilometre on land.

The LCP is a distance analysis function that finds optimal pathways between two locations, considering certain parameters such as obstacles. For instance, altitude and slope can be considered as costs that are typically avoided by travellers. In the present paper, the main variables of interest are the time taken to traverse a location, as greater travel time is generally seen as less favourable for walking. To illustrate, if a mountain range separates two locations, a person may opt to by means of a more level route. Therefore, our constraint is travel time and the LCP is employed to identify the most advantageous paths.

trade routes along these coastal cells, it would have introduced bias into our findings, favouring our primary hypothesis. This potential bias may have arisen from the increased likelihood of Aboriginal trade routes predicting economic activity, given the concentrated development along the Australian coast. Therefore, by excluding these coastal grid cells, we effectively mitigate these biases in our study.

[12] In addition to providing detailed anthropological descriptions of the origins and destinations involved in Aboriginal trade, McCarthy (1939) also produced a series of maps illustrating specific Aboriginal trade routes. We have digitally converted these maps, thus allowing us to use them as an alternative data source for our analysis in subsection 3.5.3, where we reconstruct Aboriginal trade routes using various sources.

Figure 1. Aboriginal Trading Sites and Routes in Australia

Notes: This map shows our reconstruction of the approximate location of Aboriginal trade routes in Australia, based on the work of McCarthy (1939). White lines indicate trade routes, constructed via a least cost path algorithm. Blue dots and triangles (1,026) denote trading sites (origins and destinations). Blue triangles (275) signify exclusions as part of a robustness check for analysis (see section 3.5.3.3). Trade routes were optimally constructed by authors using Özak (2018) with origins and destinations from McCarthy (1939).

Figure 1 illustrates the entire Aboriginal trade network in Australia as reconstructed by the authors based on the work of McCarthy (1939). The map reveals a vast web of trade routes encompassing the entire continent, in addition to the coastal routes.

3.2. Construction of Unit of Analysis and Outcomes

We use a grid cell of 10 km x 10 km, which covers an area of 100 km^2, as our unit of analysis. To construct an indicator of economic activity for each grid cell, we utilise data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor, which captures detailed light imagery of human-built facilities for the year 2015. This remote sensing data is filtered to exclude background noise, solar and lunar pollution, and features unrelated to electric lighting such as sunlight, glare, moonlight, aurora, fires and volcanoes, as described in Elvidge et al. (2017).

The VIIRS data differs from the widely used DMSP (Defence Meteorological Satellite Programme) nightlight data in terms of the pixel footprint, which is 45 times smaller. This improved resolution allows for more precise light data, resulting in a higher degree of accuracy when performing local analysis.

Gibson et al. (2021) compare VIIRS lights with DMSP and conclude that the former source provides a 100% less noisy relationship between city lights and GDP. Moreover, they find that DMSP data is a poor indicator of non-urban GDP as well as spatial heterogeneity of economic activity. Gibson et al. (2021) attempt to reduce this issue via a Pareto-based adjustment, however DMSP data still fails to capture much of the intra-urban heterogeneity in brightness. As such, the results make the DMSP data unsuitable for analyses that include areas such as Australian rural and desert areas. To reflect economic activity at a local level, we therefore use the VIIRS data to provide the average night-time light in each grid cell for the whole of Australia.[13,14]

In addition to luminosity data, we also construct an alternative outcome measuring population density at the grid cell level for the year 2015 by leveraging data from the Global Human Settlement Layer (GHSL). More specifically, the spatial raster dataset depicts the distribution of the residential population, expressed as the number of people at 30 arc sec resolution. We then compute the average population for each observation. Since our observations (cells) are equal areas (10 km x 10 km), the average population can also be considered as population density. Utilising GHSL urban population data offers the advantage of leveraging high-resolution satellite imagery to reassign individuals from larger, sparsely populated administrative units to areas with visible buildings, thus providing a comprehensive representation of urban populations, even in the smallest settlements (European Commission, 2023).

3.3. Covariates and Methodological Issues

Our research focuses on the question of whether Aboriginal trade routes had an influence on the development of Australian economic activities. We posit that Aboriginal people had an intimate knowledge of their environment, which enabled them to choose “efficient” routes for the exchange of goods, cultural traditions, and customs. Consequently, a key question is to identify the forces which helped determine the spatial features of Australian urbanisation: Were they determined by first-nature geography of the Australian landscape, or were they influenced, in a second-nature fashion, by Aboriginal trade routes?

In order to address the above question, we create a large dataset of geographical and climatic variables to compare grid cells independently

[13] We use the ”vcm-orm-ntl” version where the background pixels (without light) are set equal to zero.

[14] This measure can also address the phenomenon of blooming: the spillover of light onto cells tangential to the ”actual” light. In particular, to minimise the potential for spurious results due to the spread of nocturnal light, the measure increases the accuracy of our empirical analysis, reducing the problem of brightness.

of their inherent natural features. This allows us to compare areas with similar characteristics dependent upon their diverse Aboriginal trade routes. The majority of the exogenous variables are standard measures commonly found in the literature of economic development, history, and geography. These variables include the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, and a binary variable that identifies whether the cell abuts the coast.[15]

In order to further control for potential confounding factors, we introduce distance from Sydney and state capitals as control variables in our analysis. These variables, while not fully exogenous to each cell, are expected to have a significant influence on nearby locations. Moreover, we assess the distance of each cell to the nearest historical mine as an additional control variable. The historical mines were selected because the less advanced technology of the early 20th century suggests distances from those mines are irrelevant for the modern economy, given today's transport technology and infrastructure and therefore likely to be exogenous. We have excluded current mines, because their number and location could be correlated with the modern distribution of economic activity in the respective state, which would make them endogenous ”bad” controls. Still, the distance to a historical mine is also relevant, as it takes into account the gold rush period in the 19th century, which had a great impact on the economy of Australia at the local level.

Finally, we also control for water presence in each cell as a proportion of total area, providing an exogenous measure of water availability. This variable reflects economic activities that depend upon the availability of water, such as shipping, agriculture, and fishing.[16]

We examine the relationship between Aboriginal trade routes and geoclimatic variables in Table 1. We select variables that may have influenced Aboriginal people in choosing locations for their trade routes. Results show a positive but insignificant association between trade routes and distance from the sea, contrary to expectation since coastal areas are particularly suitable for human habitation. The water percentage variable exhibits a positive correlation, implying that they likely sought places with more inland water. Elevation appears to be relevant

[15]While the first layer of coastal grid cells has been excluded due to data limitations, we have created a coastal dummy using the second layer of coastal cells as we believe that these cells still offer valuable insight into the proximity of places to the coast. The exclusion of the first layer does not change the main results of the paper.

[16]We have also constructed two additional control variables to account for coastal trade patterns: historical shipwrecks and connectedness. These variables aim to capture the level of coastal trade activity and pre-industrial trading opportunities, respectively. More information about these variables, along with their sources, can be found in the Appendix, Table B.1.

Table 1. Analysis of balance: Environment and Aboriginal trade routes

	Dependent Variable: Binary variable for Aboriginal trade routes						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Agriculture Suitability	0.020						
	(0.015)						
Elevation		-0.000^{***}					
		(0.000)					
Ruggedness			-0.001^{***}				
			(0.000)				
Precipitation				-0.000			
				(0.000)			
Temperature					0.000		
					(0.000)		
Distance to the Sea						0.001	
						(0.001)	
Water Percentage							0.260^{***}
							(0.099)
N	79731	79731	79731	79731	79731	79731	79731
R^2	0.002	0.035	0.003	0.000	0.000	0.003	0.005

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell *i* has at least one Aboriginal trade route, and 0 otherwise. This variable was constructed using anthropological data from McCarthy (1939), which describes the trade routes created by Aboriginal people based on oral traditions prior to colonisation. The Human Mobility Index (HMI) from Özak (2018) was used to identify optimal routes between origins and destinations, with a least-cost algorithm. Each column includes a different geographical and climatic variable as follows: Column (1): agricultural suitability; column (2): Elevation; column (3): ruggedness; column (4): precipitation; column (5): temperature; column (6): distance to the sea; column (7): water percentage. The descriptions of the geographical and climatic variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

for Aboriginal traders, not surprisingly because it would make walking more cumbersome and so would ruggedness. Interestingly, Aboriginal people did not necessarily orientate their trade routes towards fertile plains and rain-prone areas, as the corresponding coefficients (for suitability for agriculture and rainfall) are not significant.

Table 1 does not support the hypothesis that the Aboriginal people necessarily sought access to optimal environmental conditions, since their trade routes could also lead through completely dry and non-plain regions. This indicates that their activities were not exclusively intended to exploit economically the territories traversed by the routes, but also served to link distant trading sites and thus allowed them exploit gains from trade. McBryde (2000) argues that long trade routes were an essential part of Aboriginal ceremonial life. This evidence is consistent with our findings and suggests that these expeditions enabled clans to come together, share cultural activities and communicate with each other.[17] We provide details on all covariates used in our regressions in the Notes under each table.

3.4. Empirical Strategy

To examine the impact of Aboriginal trade routes on contemporary economic activity, we estimate the following regression, with standard errors clustered at the local government level:

$$Nightlight_i = \alpha_i + \beta TradeRoutes_i + Z_i'\rho + \varepsilon_i, \tag{1}$$

where i indexes grid cells for Australia. Our dependent variable $Nightlight_i$ is a dummy variable that takes the value 1, if cell i has strictly positive nightlight (and thus economic activity), and 0 otherwise. $TradeRoutes_i$, our main variable of interest, takes the value 1, if grid cell i hosts at least one Aboriginal trade route, and 0 otherwise. Z'_i is a vector of climatic, topographic and geographic variables. In addition, our model includes fixed effects for local government districts, α_i, in order to capture any unobserved local characteristics such as market institutions. The coefficient of interest, β, reflects the impact of Aboriginal trade routes on current economic activity.

3.4.1. Main Results

Column (1) of Table 2 illustrates the relationship between Aboriginal trade routes and contemporary economic activity. We condition and cluster the data at the local government district level, and our results

[17] It should be noted that these results remain unchanged when the 25% of cells with the driest and warmest environment are excluded (see the Appendix).

are positive and significant at the 1% level. This indicates an association between higher economic activity and the presence of Aboriginal trade routes. We use latitude and longitude in column (2), and add geographical and climatic control variables in columns (3) and (4). All significant variables enter the model with the expected sign.[18] The most conservative coefficient in column (4) suggests that the probability of economic activity in a cell is 3.3% greater when an Aboriginal route is present.

In column (5) of Table 2, we utilise population density as an alternative measure of economic activity at the local level. Remarkably, the coefficient on Trade Routes remains positive and highly significant. Notably, the R-squared in column (5) is larger than in column (4). This difference can be attributed to the fact that our Night Lights measure is discrete and the alternative metric, Population Density, is continuous. Nevertheless, the fact that the key explanatory variable, Trade Routes, performs equally well confirms the robustness of our approach. Moreover, with a larger R-squared in column (5) this would suggest that Aboriginal trade routes did not only establish the foundations of local economic activity, encompassing even non-urban enclaves such as remote manufacturing and mining outposts, but also signifies their enduring "magnet" effects of permanent residents in the long-run.

Furthermore, Table A.1 in the Appendix also demonstrates that contemporary primary roads can serve as an additional measure of economic activity. Overall, our results confirm our initial hypothesis, as the sign and significance of Trade Routes and control variables follow column (4) in Table 2. Thus, our findings suggest that both higher population density and contemporary main roads in the cells with Aboriginal trade routes are indicative of greater economic activity and development.

3.5. Robustness Checks

3.5.1. Homogenising the Sample

We now focus on the robustness of our baseline results. We begin by addressing the variability that characterises the Australian landscape. Our goal is to confirm that our estimates remain robust and not affected by the heterogeneity of regions, including those with arid desert terrain. To achieve this, we excluded the top and bottom 25% of cells with the highest temperature and the lowest levels of precipitation, respectively.

Columns (1) and (2) of Table A.2 in the Appendix demonstrate that our primary variable of interest remains statistically significant even after homogenising the sample by eliminating the driest and wettest

[18] While we have excluded the first layer of coastal grid cells from the sample due to lack of data, Appendix, Section B, reports results where we also control for coastal trade dynamics.

Table 2. Baseline results

	Night Lights				Pop. Density
	(1)	(2)	(3)	(4)	(5)
Trade Routes	0.035***	0.036***	0.034***	0.030***	0.975***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.148)
Latitude		−0.000**	−0.002***	−0.003***	−0.044*
		(0.000)	(0.000)	(0.001)	(0.026)
Longitude		−0.000	0.000	0.003***	0.071**
		(0.000)	(0.000)	(0.001)	(0.033)
Agriculture Suitability			−0.002	−0.003**	−0.151***
			(0.002)	(0.002)	(0.043)
Elevation			0.000	0.000	−0.001
			(0.000)	(0.000)	(0.002)
Ruggedness			0.000**	0.000	0.009
			(0.000)	(0.000)	(0.006)
Precipitation			0.000***	0.000	0.001
			(0.000)	(0.000)	(0.001)
StDev Precipitation			0.000	0.000	0.017
			(0.000)	(0.000)	(0.012)
Temperature			0.002***	0.002**	−0.006
			(0.001)	(0.001)	(0.030)
StDev Temperature			−0.024***	−0.024***	−0.356***
			(0.005)	(0.005)	(0.121)
Coastal Dummy				0.065***	1.059***
				(0.014)	(0.289)
Distance to the Sea				−0.000	−0.015
				(0.000)	(0.010)
Distance to Sydney				0.003***	0.064*
				(0.001)	(0.035)
Distance to State Capital				0.000	−0.020***
				(0.000)	(0.007)
Distance to Historical Mine				−0.002***	−0.056***
				(0.000)	(0.010)
Water Percentage				0.007	−0.681
				(0.020)	(0.602)
Local Gov FE	✓	✓	✓	✓	✓
N	79731	79731	79731	79731	79731
R^2	0.222	0.222	0.228	0.233	0.600

Notes: The unit of observation is a grid cell of 10km X 10km. In columns (1)-(4), the dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight, and 0 otherwise. This variable uses data from Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. In column (5), the dependent variable is the logarithm of human population density, which is the number of individuals per grid cell. The data is derived from national censuses and population registers for the year 2015, with an additional minor adjustment of 1e-8 included. All columns control for local government fixed effects. Columns (1)-(5) include a measure of Aboriginal trade routes. This measure is is a dummy variable that takes the value of 1 if cell *i* has at least one Aboriginal trade routes, and 0 otherwise. This variable was constructed using anthropological data from McCarthy (1939), which describes the trade routes created by Aboriginal people based on oral traditions prior to colonisation. The Human Mobility Index (HMI) from Özak (2018) was used to identify optimal routes between origins and destinations, with a least-cost algorithm. From columns (2) to (5), geographical and climatic control variables were added gradually and incrementally. The descriptions of the geographical and climatic variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

cells. Furthermore, its magnitude is comparable to the coefficient of the baseline regression (4) in Table 2, which suggests that there is no notable distinction between coastal and inland areas in Australia.

3.5.2. Neighbouring Analysis

3.5.2.1 Along the Routes Analysis

We proceed by employing a more conservative pixel selection to perform a place-based analysis. Specifically, the analysis includes all cells intersected by trade routes as well as their respective neighbouring cells that may or may not contain a route. This approach allows us to limit the influence of cells that are too far away from trade routes, such as **un**inhabited deserts, which could act as a "noisy" control group in our primary sample.

In Table A.4, column (1) provides evidence for our hypothesis using our restricted sample. Coefficients of the main variables of interest are positive and statistically significant. Fixed effects for local governments are included for all pixels along trade routes and their neighbourhoods, facilitating comparison of environmentally similar cells with the only difference being the presence of Aboriginal trade routes. While this test is a step towards excluding local effects other than trade routes, we acknowledge that local governments are incomparably larger in many parts of Australia. To address this, the contiguous pair analysis in section 3.5.2.2 eliminates any prospective unobserved local effects.

3.5.2.2 Contiguous Pair Analysis

We now take into account the unobservable characteristics of cells with an Aboriginal trade route, which may have allowed them to attract more population and economic activity in the long term. To this end, we utilise the approach similar to Dube et al. (2010) and Michalopoulos and Papaioannou (2013) and perform a contiguous pair analysis. Specifically, we develop a estimation model that includes all 10 km x 10 km cells hosting Aboriginal trade routes and their neighbouring cells without routes. For example, if cell A has an Aboriginal trade route and is adjacent to or shares a corner with cells B and C without routes, both pairs will be included in our sample. Our specification for adjacent cells includes a fixed effect for each pair in order to attribute any difference in contemporary economic activity between the two cells to Aboriginal trade routes. The specification for contiguous pair cells is as follows:

$$Nightlight_{i,(j)} = \alpha_{i,(j)} + \beta TradeRoutes_{i,(j)} + Z'_{i,(j)}\rho + \varepsilon_{i,(j)}. \tag{2}$$

In equation (2), our dependent variable is a dummy variable that takes the value 1 when there is nightlight in cell i, which contains

Aboriginal trade routes, and is also adjacent to cell j, which does not contain a route. The same structure applies to the $TradeRoutes$ and all control variables $Z'_{i,(j)}$. Finally, $\alpha_{i,(j)}$ are the pairs-fixed effects.

Column (2) of Table A.4 presents the results of our analysis with contiguous pair cells. The coefficient of the variable for Aboriginal trade routes is positive and statistically significant at the 99% confidence level. This finding indicates that Aboriginal trade routes retain a significant influence on current economic activity even after taking into account the majority (if not all) of unobserved characteristics between the 10 km x 10 km cells in the same region of Australia.

3.5.3. Measurement Error and Alternative Indicators

3.5.3.1 Cell Size Analysis

Indeed, our analysis at the 10-to-10-km level could also be another source of concern due to measurement errors resulting from the construction of our main binary variable based on the Human Mobility Index (HMI). To address this, we extend our cells to 50-to-50-km to account for potential inaccuracy in the location of trade routes. This provides us with an area of 2500 km^2 to test our results. Table A.3 shows positive and significant impacts of Aboriginal trade routes on current economic activity in all columns, with column (4) representing our most conservative specification, where only the cell size differs, but all covariates remaining the same. The effect is larger than the corresponding value, reported in Table 2, suggesting that our main estimates are close to the lower bound.

3.5.3.2 Alternative Sources of Measurement Error

One more potential source of measurement error is that our baseline results rely on just one source of data, namely McCarthy (1939), for the location of Aboriginal trade routes. This is problematic because the HMI may not precisely reflect the travel patterns of Aboriginal people. To address this issue, we employ a number of strategies. First, we collect data on the locations of Aboriginal rock art to proxy for the existence of human activity in Australia prior to European arrival. We use the Aboriginal rock art data and the HMI as the main parameters in our weighted least-cost path algorithm and construct a dummy variable for the trade routes thus defined to examine its effects on current economic activity. In Table A.5, column (1), the new dummy variable has a statistically significant positive coefficient, indicating that our results are consistent with alternative data sources on the location of Aboriginal trade routes.

Second, we reconstruct the Aboriginal trade routes by adding information on the historical maps of McCarthy (1939). To supplement the detailed anthropological analysis of the hundreds of Aboriginal trade routes that McCarthy (1939) used in his data, he also produced a series of maps that depict what these routes may look like in Australia. We subsequently digitised and georeferenced these maps. As shown in Figure A.1 in the Appendix, the number of Aboriginal trade routes appears to be smaller than that of the georeferenced map in Figure 1. This discrepancy is unexceptional, as McCarthy (1939) only endeavored to identify some of the trade routes. However, we assume that the most significant routes are included, even if not all have been visually documented.

Importantly, we then weighted the algorithm for the least-cost path using both the historical map of McCarthy (1939) and the data from Aboriginal rock art, and McCarthy's map alone. Columns (2) and (3) of Table A.5 present the results, which indicate that each source (or combination) of our historical sources provides alternative sets of Aboriginal trade routes that influence current economic activity at the local level.

Finally, we conduct an analysis to assess to what extent our main dataset, comprised of the reconstructed trade routes based on the HMI, agrees with the three other datasets on trade routes based on, one, the HMI & Rock Art (RA); two, McCarthy's historical maps (DIG) & RA; and three, DIG. For example, using our main dataset, which comprises only data from the HMI, and a dataset containing information from both the HMI and the RA, we kept cells whose locations relative to an Aboriginal trade route in Australia matched in both datasets. Columns (4)-(6) of Table A.5 indicate that, even when excluding trade routes with potential measurement errors, our findings remain consistent with the baseline. All coefficients for Aboriginal trade routes are positive and statistically significant at the 1% level.

3.5.3.3 Trading Sites

While we addressed measurement error in constructing the Aboriginal trade routes in the previous section, some may argue that significant noise remains. Specifically, some may argue that the routes estimated by the least cost path algorithm are not the actual trails that Aboriginal people used to travel from origins to destinations. To test the credibility of our variable of interest, we focus on all starting and destination sites collected by McCarthy (1939). Specifically, we investigate whether economic activity is more likely to be observed in locations where Aboriginal people traded goods in the past.

Moreover, we believe that the above analysis allows for a sharper identification of the effects of Aboriginal trade routes on long term economic activity. Since our data on trading sites (i.e., starting or destination points of trade routes) covers the entire Australian territory, we can exclude all coastal areas, thereby focusing on the interior, which was the most unfamiliar and difficult to traverse area for European colonisers. Any association between early trading sites and contemporary economic activity would therefore clearly indicate that Europeans selected their settlement locations based on Aboriginal knowledge of the landscape.

Therefore, we conduct an alternative estimation of equation (1) by replacing our main variable of interest, which is based on estimated trade routes, with a dummy variable that takes the value of 1, if at least one Aboriginal trading site is present in a cell, and 0 otherwise. Anticipating our detailed analysis, we think that by using reported Aboriginal trading sites we avoid relying on estimated routes and thus offer robust evidence in support of our claim. In Panel A of Table 3, column (1) shows a positive and strong relationship between Trading Sites and Night Lights when all cells in the sample are used.

We extend the analysis in columns (2)-(6) of Table 3 in Panel A by gradually excluding all grid cells that are 50 km, 100 km, 200 km, 300 km and 500 km from the coastline, respectively, to narrow down our sample. Column (2) shows the results with the least restrictive sample, which excludes only cells within 50 km of the coastline. As a result, 275 trading sites are excluded. These sites are marked by blue triangles in figure 1. The respective coefficient is positive and significant, indicating that our results are not predominantly influenced by proximity to the coast. Notably, this is a remarkable result given that major Australian cities such as Sydney and Melbourne, which might coexist with coastal trading sites due to their natural resource abundance, have already been dropped. The next four columns report results with successively more restricted samples, leaving only 25% of interior Australian locations. However, the respective coefficients remain positive and significant. Therefore, we argue that we have dispelled concerns that economic activity by European colonizers and pre-colonial Aboriginal trading activity coincided randomly.

In Panel B of Table 3, we repeat the same analysis from Panel A with population density as the main dependent variable instead of Night Lights. The coefficient on Trading Sites once more demonstrates statistical significance at the 1% threshold. This analysis effectively allays several important concerns. First, it dispels doubts that our main outcome—Night Lights—is not accurately reflecting economic activity within inland locations across Australia. The observed brightness seems to stem not from places like mines, factories, or power plants, but predominantly from agglomerated residential locations. Second, we mitigate concerns that our results could be influenced by biases related to Australia's coastal development — a region where a significant

Table 3. Trading Sites

Panel A:	Dependent Variable: Binary dummy for night light					
	(1) all cells	(2) excl. 50km	(3) excl. 100km	(4) excl. 200km	(5) excl. 300km	(6) excl. 500km
Trading Sites	0.197^{***}	0.168^{***}	0.168^{***}	0.169^{***}	0.159^{***}	0.070^{***}
	(0.023)	(0.026)	(0.028)	(0.029)	(0.033)	(0.020)
Local Gov FE	✓	✓	✓	✓	✓	✓
Geo & Hist Controls	✓	✓	✓	✓	✓	✓
N	79731	72474	65382	52803	41838	23744
R^2	0.234	0.167	0.151	0.113	0.063	0.032
Panel B:	**Dependent Variable: Population Density**					
	(1) all cells	(2) excl. 50km	(3) excl. 100km	(4) excl. 200km	(5) excl. 300km	(6) excl. 500km
Trading Sites	4.087^{***}	3.863^{***}	3.814^{***}	3.909^{***}	3.692^{***}	3.051^{***}
	(0.358)	(0.429)	(0.469)	(0.569)	(0.607)	(0.439)
Local Gov FE	✓	✓	✓	✓	✓	✓
Geo & Hist Controls	✓	✓	✓	✓	✓	✓
N	79731	72474	65382	52803	41838	23744
R^2	0.600	0.582	0.570	0.529	0.477	0.281

Notes: The unit of observation is a grid cell of 10km X 10km. In Panel A, the dependent variable is a dummy variable that takes the value of 1 if cell i has nightlight,and 0 otherwise. This variable uses data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. In Panel B, the dependent variable is the logarithm of human population density, which is the number of individuals per grid cell. The data is derived from national censuses and population registers for the year 2015, with an additional minor adjustment of 1e-8 included. Trading Sites is a dummy variable that takes the value of 1 if at least one Aboriginal trading point is present in each cell and 0 otherwise. In column (1), all grid cells in the sample are used. From columns (2)-(6), cells are progressively excluded that are 50km (col. 2), 100km (col 3), 200km (col 4), 300km (col 5) and 500km (col 6) close to the shoreline. All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

portion of the Australian population is concentrated, and most notably along the Eastern Seaboard. Specifically, 85% of Australian population lives within 50km of the coast, which we have actually excluded in column (2). Third, we systematically address concerns regarding the accessibility of coastal areas by sea, for which the adoption of Aboriginal knowledge by Europeans would have been irrelevant. Fourth, we take steps to alleviate concerns regarding the potential influence of the spatial distribution of Aboriginal trade routes intersecting with present-day population, which predominantly align with coastal areas. Fifth, comparing across from column (1) to column (6) we see that the estimated coefficient of trading sites remains very significant and falls numerically by only 25%. This dispels the notion that the informational impact of trading sites on contemporary urban density is confounded by proximity to the coast.[19]

3.5.4. Network-Based Robustness Check

We also seek to examine the robustness of our Trade Routes variable by considering as alternative additional controls a number of centrality measures for the network of Aboriginal routes. As we documented earlier, the trade routes were used for numerous cultural activities in addition to trade. If we were to assume that the Aboriginal communities, associated with origins and destinations, used the trade routes for the purpose of exchange of commodities that were differentiated by origin, we may study the resulting trading system by the tools of international trade. That is, following Allen and Arkolakis (2014) and Chen et al. (2022), we may obtain a network description of the trade routes. This allows us to define centrality measures, based on the matrix with elements the inverse traveling costs, $\mathbf{T} = [1/\tau_{ij}]$. as computed earlier.

We examine alternative measures of centrality as follows: degree, betweenness, Katz-Bonacich, and eigenvector centrality (Bloch et al., 2021). Degree is the most local of them, and in our setting is equivalent to the average inverse distance from each node to every other node. Eigenvector is the most global in the sense that it aggregates the centrality of every other node. Betweenness and Katz-Bonacich fall in between. The latter assigns a basic centrality to all nodes and accounts for the "lengths" of paths by discounting them in order obtain a finite measure. Its extreme values coincide with eigenvector centrality.

Table A.7 in Appendix reports estimation results with those centrality measures as alternative controls. Interestingly, their inclusion always yields highly significant coefficients, and in most cases slightly

[19] In order to provide supplementary validation for these concerns, we undertake an additional check. In Table A.6, we use as our main variable of interest—Aboriginal trade routes, that is, instead of Trading Sites, with regression models mirroring those reported by Table 3. The coefficients presented in Table A.6 further strengthen the main results of the paper.

strengthens the coefficient of Trade Routes, thus reaffirming its robustness.

3.5.5. Robustness Checks: Extensions

We conclude this section by performing further robustness checks. First, we exclude all origin and destination points (cells) of Aboriginal trade routes from our sample. Mćcarthy (1939) refers to these places as trading points, and they might have developed into modern centers of economic activity (cities or towns). Thus, by excluding them, we distinguish between the effects of pre-colonial trading points and trading routes. Similarly, we create buffers with a diameter of 50 km (beam 25 km) around the trading sites and exclude all cells within these buffers. Table A.8, columns (1) and (2), show that the coefficient of interest remains economically and statistically significant after excluding pixels associated to origins and destinations, and while using the 50 km buffer.

Second, Australia, a vast continent, is microgeopraphically very diverse as compared to Europe. To underscore this point, we note that Western Australia is mainly composed of sandy and sparsely populated deserts; New South Wales is heavily urbanised and hosts large cities such as Sydney. In order to test whether there is any particular state that could influence our results, we exclude sequentially each of the states individually in Table A.9. The coefficients associated with our main variable demonstrate that despite microgeographic and environmental heterogeneity across Australian states, Aboriginal trade routes maintain their positive and significant effect.

Third, we assess the potential impact of spatial autocorrelation on our results by using the large-cluster approach, as proposed by Bester et al. (2011) and implemented by textcitekelly2020direct The latter conducts a Monte Carlo simulation and finds that the large-cluster approach with three clusters provides rather conservative and robust estimates for different patterns of spatial correlation. As Table A.10 shows, the spatially corrected coefficient suggests that the results of our study are unlikely to be driven by spatial autocorrelation.

Fourth, we apply the technique proposed by Oster (2019) that accounts for omitted variable bias. This technique yields estimates that are 30% higher in terms of R^2 than the most conservative estimate. In particular, it assumes that the selection of observed controls is proportional to the selection of unobserved controls and allows the calculation of a new β coefficient and a parameter δ. To rule out the case of omitted variable bias, the numbers between our conservative estimate and the new β coefficient should safely exclude zero and the parameter δ should be greater than one. Theoretically, the parameter indicates how large the unobservable variables should be relative to the observable variables in order to obtain a biased model. If it is greater than one, the method of Oster (2019) assumes that the estimates are very unlikely to be affected by omitted variable bias. Table A.11 shows that both conditions are met, with the new β coefficient being very close to that of our baseline estimate and the parameter δ being greater than 6. This suggests that our model is very unlikely to be affected by omitted variable bias.

Finally, we use the spatial first differences (SFD) design proposed by Druckenmiller and Hsiang (2018). This method accounts for the fact that adjacent units of analysis that are spatially closer to each other offer better counterfactuals, as unobservable confounders are not systematically correlated between them. To this end, we compare cell c to cell $c-1$ and assume that the expected potential outcome for each would be the same if they received the same treatment. We then distinguish each pair of adjacent cells in both west-east and north-south directions and regress the spatial first differences as follows:

$$\Delta Luminosity_i = \beta_{fsd} TradeRoutes_i + \varepsilon_i. \tag{3}$$

In equation (3), β_{fsd} captures the effect on luminosity when random cell c is treated while cell $c-1$ is not (or vice versa). Omitted by default is a hidden factor Y_{fsd} Cov, a vector of covariates for each observation (cell). Column (1) of Table A.12 calculates the differences in the west-east direction and column (2) calculates the differences in the north-south direction. We observe a positive and statistically significant effect of Aboriginal trade routes on current economic activity. This result lends confidence that spatially correlated unobserved heterogeneity and omitted variables are not biasing our findings.[20]

4. Urban Evolution of Australia

In this section, we examine the dynamic effects of Aboriginal trade routes on the settlement of new populations in Australia. This analysis allows us to investigate the possible shift in informational significance of these routes in the face of other historical shocks, such as the gold rush between the 1850s and 1910s, World War II, and contemporary migration in the 20th century. This is important to consider because while early European settlements such as Sydney or Melbourne may have had their roots in Aboriginal people, this is less likely to be the case for later settlements.

To examine the above argument, we use data from Kampanelis (2019) on the year of establishment of 249 major cities in Australia,

[20] Our results remain highly significant when bootstrapped standard errors are used (Roodman et al., 2019)

Table 4. Establishment of Cities

	All Cities	Cities est. before 1850	Cities est. in 1850-1900	Cities est. in 1900-1950	Cities est. in 1950-2000
	(1)	(2)	(3)	(4)	(5)
Trade Routes	0.004***	0.001*	0.002***	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Local Gov FE	✓	✓	✓	✓	✓
Geo & Hist Controls	✓	✓	✓	✓	✓
N	79731	79731	79731	79731	79731
R^2	0.054	0.089	0.029	0.018	0.010

Notes: The unit of observation is a grid cell of 10km X 10km. OLS estimates are shown with robust standard errors clustered at the local government district level. In column (1), the dependent variable is a dummy variable that takes the value of 1 if cell *i* has a major city that was established by Europeans between 1788 and 2000 in Australia. In column (2), the dependent variable is a dummy variable that takes the value of 1 if cell *i* has a major city that was established by Europeans between 1788 and 1850. In column (3), the dependent variable is a dummy variable that takes the value of 1 if cell *i* has a major city that was established by Europeans between 1850 and 1900. In column (4), the dependent variable is a dummy variable that takes the value of 1 if cell *i* has a major city that was established by Europeans between 1900 and 1950. In column (5), the dependent variable is a dummy variable that takes the value of 1 if cell *i* has a major city that was established by Europeans between 1950 and 2000. Dummy variables from all columns were constructed using data from Kampanelis (2019) on the year of establishment of 249 major cities in Australia. All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. The constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

which comprise a large portion of the total population. To analyse this data, we partition the cities into four groups according to their year of establishment: cities established before 1850 (from 1788), between 1850 and 1900, between 1900 and 1950, and between 1950 and 2000. We then create four dummy variables for each cell by assigning the value 1 if cell "i" is associated with one of these groups of cities and use them as dependent variables.

In Table 4, we report results of regressing the dummy variables for the year when a city was founded against the presence of Aboriginal trade routes. Results in column (1), which includes all cities, are positive and significant at the 99% confidence level. Columns 2 and 3 reveal that Aboriginal trade routes have a positive and significant effect on cities established before 1900. However, this effect does not extend to later years; cities established after 1900 do not show a significant effect from these trade routes. This finding is in accordance with the notion that the likely effects of technological progress, population growth, oil discoveries and other parameters, which have enabled the establishment of cities in locations that were previously inhospitable for human settlement, have rendered the informational advantage of Aboriginal knowledge obsolete.

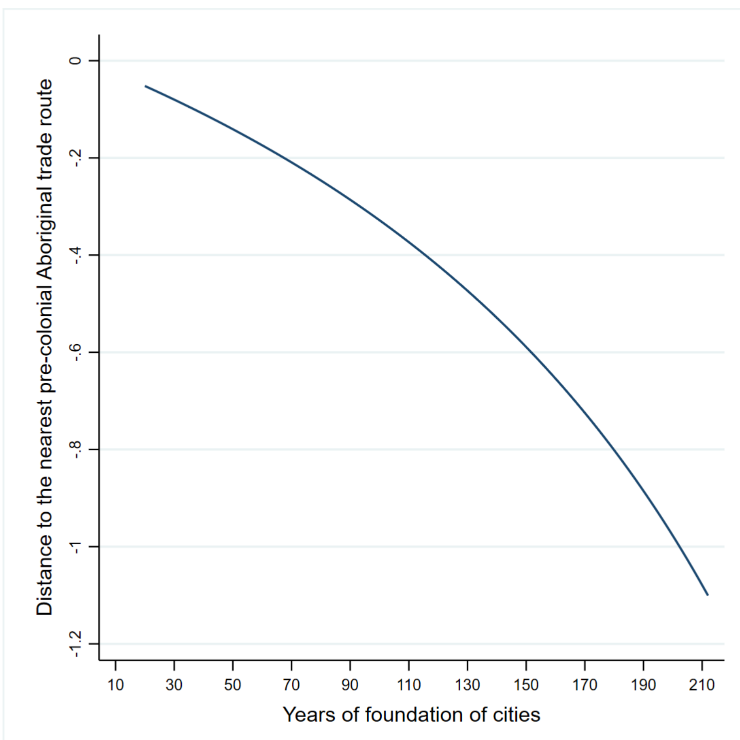

Figure 2. Urban evolution and proximity to Aboriginal trade routes

Notes: This figure shows the marginal association between the distance to the nearest Aboriginal trade route to major cities and the year of establishment of major cities in Australia. Data on the years cities were founded comes from Kampanelis (2019).

In order to further explore the spatial patterns of cities in relation to temporal dimension, we calculated the distance of each city from the nearest Aboriginal trade route. Subsequently, we used Stata's marginsplot command to examine the relationship between the spatial pattern of the cities (distance to an Aboriginal trade route) and the year a city was founded. The results in Figure 2 demonstrate a concave decreasing pattern, implying that during the European colonisation, cities were situated closer to Aboriginal trade routes, while this relationship gradually weakened over time.

5. Mechanisms and Path Dependence

The evidence has firmly established a robust positive relationship between Aboriginal trade routes and contemporary economic activity. This section aims to empirically investigate the potential mechanisms underlying this relationship. Specifically, we posit that the influence of Aboriginal trade routes on the modern Australian economy may be partly attributed to path dependence and agglomeration effects resulting from the development of early European transportation infrastructure, which closely followed these routes. This fact is well supported by recent anthropological evidence (Kerwin, 2010). Importantly, and in line with the historical findings presented in section 2, when Europeans established settlements in new regions, they constructed transportation networks to connect these areas to larger colonies. This development likely facilitated the concentration of economic activities by enhancing connectivity over time.

The mechanism described above is consistent with recent studies examining the impact of historical trade routes on contemporary outcomes (Dalgaard et al., 2018; Flückiger et al., 2021; Ahmad and Chicoine, 2021). These studies argue that regions that experienced a higher degree of exposure to these trade networks developed better connectivity patterns due to reduced transport costs, leading to increased levels of goods exchange and subsequent infrastructure investments. As a result, these regions presently exhibit higher economic outcomes than those with a lower legacy of historical trade routes.

To assess the mechanism, we digitised and georeferenced maps of early transport infrastructure in Australia. Figure A.3 depicts all early railways built between 1880 and 1920, which was created using a series of historical maps. Similarly, Figure A.4 displays all early highways constructed by Europeans until the early 1950s, with only the major interstate and state highways in Australia being digitised. We construct dummy variables for each map to measure the presence of early transport networks in Australia. For instance, we measure early railway infrastructure by assigning a dummy variable of 1 to grid cells

Table 5. Mechanisms

	Early Railways	Early Highways
	(1)	(2)
Trade Routes	0.013**	0.021***
	(0.006)	(0.007)
Local Gov FE	✓	✓
Geo & Hist Controls	✓	✓
N	79731	79731
R^2	0.200	0.137

Notes: The unit of observation is a grid cell of 10km X 10km. OLS estimates are shown with robust standard errors clustered at the local government district level. In columns (1), the dependent variable is a dummy variable that takes the value of 1 if cell *i* has at least one railway built between 1880 and 1920, and 0 otherwise. In column (2), the dependent variable is dummy variable that takes the value of 1 if cell *i* has at least one highway built in Australia until the early 1950s, and 0 otherwise. The measure uses only major interstate and state highways. Both measures were constructed by digitising and georeferencing a series of historical maps, with sources provided in the description of variable section in the Appendix. All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. The constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

with at least one railway and 0 otherwise. This methodology is similarly applied to the other map on early highways.

We regress each of our dummies on our main variable of interest, as well as all of our baseline control variables and local government fixed effects in Table 5. Columns (1)-(2) show that both early railways and highways were significantly influenced by Aboriginal trade routes. The historical evidence we provide is consistent with these results, suggesting that contemporary development is associated with Aboriginal trade routes. In other words, Europeans relied on Aboriginal knowledge of the landscape in the settlement of Australia.

6. Adoption of Aboriginal Knowledge or Geography?

In this final section, we turn our attention to establish the plausibility of our identification assumption. We contend that the adoption of Aboriginal knowledge of the landscape influenced European exploration and settlement. The construction of transportation infrastructure reinforced the path dependence evident in the preceding discussion. It thus shaped the spatial distribution of Australian modern economic activity in profound ways.

However, an important concern arising from our empirical findings relates to the distinction between the adoption of Aboriginal knowledge, on the one hand, and the direct effects of inherent characteristics of the Australian topography and the indirect effects of how the Aborigines gained that knowledge, on the other. Specifically, it remains essential to ascertain whether our results genuinely reflect such adoption or they can be attributed to other favorable environmental attributes that may have guided European preferences during their exploration of Australia. In such a scenario, Europeans did not have to adopt the routes used by Aboriginal people. For instance, while Europeans established early cities in arid regions such as Alice Springs, which developed due to the establishment of the Overland Telegraph Line in the 19th century (and not as a result of the gold rush), other ecotopias like the Daintree Rainforest, and Cape York Peninsula have remained largely unsettled or sparsely populated until the 21th century.

Therefore, we seek to demonstrate empirically that Australia's economic trajectory would have followed different geographical patterns if Europeans had not adopted Aboriginal knowledge. A contrary finding would suggest that Aboriginal trade routes had limited or insignificant influence on how Europeans chose sites for exploration and settlement.

To address these concerns and validate our identification strategy, we leverage exogenous variation in European exploration and settlement across Australia. To this end, we follow Barjamovic et al. (2019), Optimal Travel Routes, Online Appendix, pp. 10–11, and construct

Table 6. Natural Routes *versus* Aboriginal Trade Routes

	European exploration	All Cities	Early Railways	Early Highways	Night Lights	Pop. Density
	(1)	(2)	(3)	(4)	(5)	(6)
Natural Routes	0.006^{*}	0.000	0.001	0.010^{***}	0.004^{***}	0.099^{***}
	(0.003)	(0.000)	(0.001)	(0.004)	(0.001)	(0.032)
Aboriginal Trade Routes	0.017^{***}	0.001^{***}	0.004^{**}	0.006^{***}	0.009^{***}	0.282^{***}
	(0.003)	(0.000)	(0.002)	(0.002)	(0.002)	(0.043)
Local Gov FE	✓	✓	✓	✓	✓	✓
Geo & Hist Controls	✓	✓	✓	✓	✓	✓
N	79731	79731	79731	79731	79731	79731
R^2	0.069	0.054	0.200	0.138	0.233	0.600

Notes: The unit of observation is a grid cell of 10km X 10km. OLS estimates are shown with robust standard errors clustered at the local government district level. All columns show standardised coefficients. Natural Routes is the logarithm of the number of optimal travel routes that intersects within each pixel. Aboriginal Trade Routes is a dummy variable that takes the value of 1 if cell i has at least one Aboriginal trade route, and 0 otherwise. In column (1), the dependent variable is an indicator that takes the value of 1 if there exists at least one European exploration route in a grid cell, and 0, otherwise. In column (2), the dependent variable is a indicator that takes value of 1 if grid cell i is associated to the establishment of a city in Australia between 1788 and 2000, and 0 otherwise. In column (3), the dependent variable is an indicator that takes value 1 if at least one railway was built in grid cell i between 1880 and 1920, and zero otherwise. In column (4), the dependent variable is an indicator that takes value 1 if at least one highway was built in grid cell i until the early 1950s, and zero otherwise. In column (5), the dependent variable is an indicator that takes the value of 1 if grid cell i has nightlight, and 0 otherwise. In column (6), the dependent variable is the logarithm of human population density, which is the number of individuals per grid cell. The data is derived from national censuses and population registers for the year 2015, with an additional minor adjustment of 1e-8 included. All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. The constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

Natural Routes in Australia. These routes include geographically intrinsic routes that extend inland from each to every other coastal grid cell. Specifically, we train our least-coast path algorithm to identify optimal travel paths between all pairs of coastal pixels. The number of intersections of these travel paths with each pixel indicates its degree of connectedness, i.e. better Natural Routes. Our measure of Natural Routes is then defined as the logarithm of the number of optimal routes that intersects with each pixel. Figure 3 shows the heat map with the values for Natural Routes, where high density means higher connectivity. Since this measure uses the HMI index as a ”travel cost” parameter, it can be considered exogenous to any human activity. Thus, our variable Natural Routes exogenously represents optimal locations for travel and settlement in Australia.

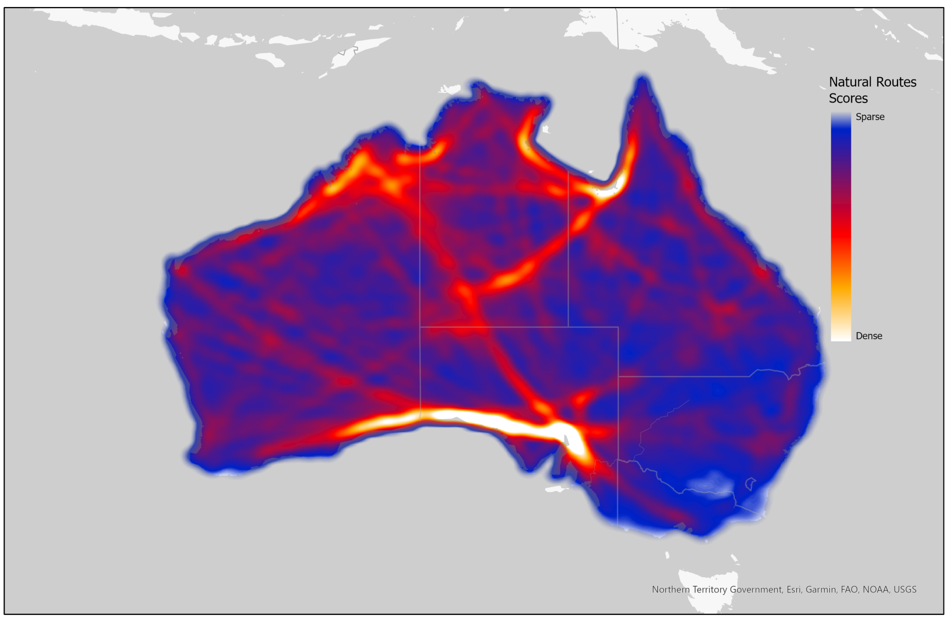

Figure 3. Natural Routes Scores

Notes: This heat map shows the ratings of Natural Routes in Australia. The routes were created using a least cost path algorithm to identify optimal travel routes from each coastal pixel to the interior. The routes were optimally constructed by the authors using the Human Mobility Index of Özak (2018).

We begin by testing the extent to which Europeans relied on Natural Routes or Aboriginal trade routes when exploring and settling Australia. To do so, we digitise the map published by Robinson (1927) showing all early European inland explorations routes from 1606 to 1901 (see Figure A.2 in the Appendix).[21] We then construct a dummy

[21]Although this is a detailed map showing both nodes and sections of the early explorations, we should also note the limited technology of geographical tools in the early 20th century.

variable, Exploration Routes, that takes the value 1 if there is at least one European exploration route in a grid cell and 0 otherwise, and use it as a new dependent variable.

Table 6 presents the results of a"horse race" analysis, comparing the predictive performance of Natural Routes and Aboriginal Trade Routes in explaining the patterns of European exploration, settlement, and the evolution of modern economic activity in Australia. The reported coefficients in Table 6 are standardised, providing insights into the statistical power and effect size of both variables. Therefore, these coefficients reflect the change in the outcome variables associated with a one-standard deviation increase in the predictor variables.

The results are surprising. Examining the coefficients in column (1) of Table 6, we observe that a one-standard deviation increase in Natural Routes corresponds to a significantly smaller effect (approximately one-third) on Exploration Routes compared to our main measure of Aboriginal Trade Routes. Moreover, it is noteworthy that the coefficient on Natural Routes exhibits statistical significance only at the margins, while the estimate for Aboriginal Trade Routes remains significant at the 1% level. In column (2), we explore the effects of these variables on the patterns of urban settlement in Australia. The dependent variable in column (2) is the dummy variable, defined in Section 4, that identifies the 249 largest cities (established from 1788 to 2000). The coefficient on Natural Routes is statistically insignificant while the one capturing the effects of Aboriginal trade routes continues showing a strong statistical association.

Columns (3)-(6) of Table 6 then examine the effects of Natural Routes and Aboriginal Trade Routes on historical railways in column (3), where the coefficient on Natural Routes once again is not statistically significant. However, the coefficient on Aboriginal Trade Routes remains highly significant, underscoring its importance on the development of historical railways during colonisation as noted in Section 2.

Moving to columns (4)-(6) of Table 6, we find statistically significant effects for both Natural Routes and Aboriginal Trade Routes. Notably, the effect is larger when predicting the establishment of early highways, but when evaluating nighttime light density and population density, the effect of Natural Routes is approximately half as large as the effect attributable to Aboriginal trade routes. [22]

The results presented in this section provide compelling support for the hypothesis that the adoption of Aboriginal knowledge by Europeans during colonisation significantly contributed to the spatial patterns of modern urbanisation and economic activity in Australia. However, it is crucial to acknowledge that while both Natural Routes and Aboriginal

[22] We have also tested for equality between the two variables. The coefficients on the Natural Routes and Trade Routes are statistically different.

Trade Routes are statistically significance Natural Routes are numerically more important for early highways, which makes sense in view of engineering design considerations. This suggests that other factors also contribute to our understanding of how Australia's economy unfolded over time.

7. Conclusion

This paper documents the long-term economic impact of the adoption of local knowledge by Europeans in their colonial expansion. We focus on a unique "natural" experiment in colonial Australia and argue that Europeans relied on Aboriginal knowledge of the landscape for their exploration and settlement. Drawing on anthropological studies that highlight the role of Aboriginal trade routes in European settlement of inland Australia during the colonial period, we construct a novel dataset of Aboriginal trade routes and trading sites and examine their influence on contemporary economic activity.

Our analysis demonstrates that regions with access to Aboriginal trade routes are associated with higher economic activity today. We show that our results are not driven by geographical variation, unobserved characteristics of neighbouring cells, measurement errors in the reconstruction of Aboriginal trade routes, spatial autocorrelation, and omitted variable problems.

We also present evidence indicating that Aboriginal trade routes had a significant influence on the establishment of major Australian cities between 1788 and 1900, but not on those established in later years. This finding is consistent with our argument that early Australian settlements were founded in locations served by those routes. Moreover, the trend of cities being founded near Aboriginal trade routes appears to diminish over time. In conclusion, these findings provide support for the claim that Aboriginal trade routes had a dynamic effect on the formation of new population centres in Australia.

We demonstrate that the transport infrastructure built by Europeans linking early settlements to key colonies in Australia may explain the positive relationship between Aboriginal trade routes and contemporary economic activity. This is consistent with recent literature examining the long-term impacts of historical trade routes, which suggests that such infrastructure may have resulted in a higher concentration of economic activity due to better connectivity. We empirically demonstrate that historical railways and early highways are positively associated with these routes.

Finally, we validate our identification assumption that Aboriginal knowledge influenced European exploration and settlement in Australia, shaping its modern economic activity. Specifically, we address the concern that our findings may be driven by the inherent characteristics of the Australian topography rather than Aboriginal knowledge. To address this, we utilise exogenous variation in European exploration and construct "Natural Routes" in Australia, representing optimally defined geographical travel paths from each coastal point to every other coastal point through the interior of Australia. Our analysis shows that Aboriginal trade routes predict European exploration better than optimally drawn Natural Routes. While Natural Routes have limited impact on European settlement and historical railways, Aboriginal trade routes remain significant. Furthermore, the effect of Natural Routes on night light density is half that of Aboriginal trade routes. Overall, our findings indicate that Aboriginal knowledge played an important role in shaping modern urbanisation and economic activity in Australia.

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Appendices

A. Tables and Figures

Table A.1. Additional measure of modern economic activity

	Dependent Variable: Primary Roads
	(1)
Trade Routes	0.103***
	(0.023)
Local Gov FE	✓
Geo & Hist Controls	✓
N	79731
R^2	0.344

Notes: The unit of observation is a grid cell of 10km X 10km. OLS estimates are shown with robust standard errors clustered at the local government district level. The dependent variable is dummy variable that takes the value of 1 if cell *i* has a primary road. The specific sources for these two variable can be found in the Appendix. Column controls for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. The constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

Table A.2. Homogeneous sample

	Dependent Variable: Binary variable for night light	
	(1)	(2)
	≥25% Precipitation	≤25% Temperature
Trade Routes	0.041***	0.025***
	(0.006)	(0.006)
Local Gov FE	✓	✓
Geo & Hist Controls	✓	✓
N	59457	59678
R^2	0.238	0.253

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight, and 0 otherwise. This variable uses data from Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. In column (1), cells with the bottom 25% rainfall and temperature were excluded. In column (2), cells with the top 25% rainfall and temperature were excluded. All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

Figure A.1. Aboriginal trade routes in Australia: McCarthy's maps

Notes: This map shows Aboriginal trade routes in Australia, based on the work of McCarthy (1939). Red lines indicate trade routes. Authors' own digitalisation using McCarthy (1939)

Table A.3. 50 X 50 km cell analysis

	Dependent Variable: Binary variable for night light			
	(1)	(2)	(3)	(4)
Trade Routes	0.051**	0.056**	0.055**	0.048**
	(0.023)	(0.023)	(0.024)	(0.023)
Latitude		−0.022***	−0.024	−0.051
		(0.008)	(0.027)	(0.046)
Longitude		−0.011	−0.011	0.089**
		(0.015)	(0.015)	(0.045)
Agriculture Suitability			−0.010	−0.074*
			(0.026)	(0.044)
Elevation			0.000	−0.000
			(0.000)	(0.000)
Ruggedness			−0.000	−0.001
			(0.001)	(0.001)
Precipitation			0.000	−0.000*
			(0.000)	(0.000)
StDev Precipitation			0.001**	0.001***
			(0.000)	(0.000)
Temperature			−0.000	−0.005
			(0.004)	(0.003)
StDev Temperature			0.014	0.019
			(0.022)	(0.022)
Coastal Dummy				0.117**
				(0.046)
Distance to the Sea				0.000
				(0.001)
Distance to Sydney				0.010*
				(0.005)
Distance to State Capital				0.002**
				(0.001)
Distance to Historical Mine				−0.012***
				(0.001)
Water Percentage				0.005
				(0.004)
Local Gov FE	✓	✓	✓	✓
N	3444	3444	3444	3444
R^2	0.286	0.289	0.294	0.334

Notes: The unit of observation is a grid cell of 50km X 50km. The dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight, and 0 otherwise. This variable uses data from Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. All columns control for local government fixed effects. Columns (1)-(4) include a measure of pre-colonial Aboriginal trade routes. This measure is is a dummy variable that takes the value of 1 if cell *i* has at least one pre-colonial Aboriginal trade routes, and 0 otherwise. This variable was constructed using anthropological data from Mćarthy (1939), which describes the trade routes created by Aboriginal people based on oral traditions prior to colonisation. The Human Mobility Index (HMI) from Özak (2018) was used to identify optimal routes between origins and destinations, with a least-cost algorithm. From columns (2) to (4), geographical and climatic control variables were added gradually and incrementally. The descriptions of the geographical and climatic variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

Table A.4. Neighbouring analysis

	Dependent Variable: Binary variable for night light	
	(1)	(2)
Trade Routes	0.030***	0.014***
	(0.006)	(0.002)
Local Gov. FE	✓	✓
Geo & Hist Controls	✓	✓
N	18188	115024
R^2	0.233	0.465

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell i has nightlight, and 0 otherwise. This variable uses data from Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. Column (1) excludes from the sample cells with Aboriginal trade routes and all their tangents that may or may not host a pre-colonial trade route. Column (2) is regression based on an analysis of contiguous pairs, which include pair-fixed effects, following equation equation 2 from section 3.5.2.2. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

Figure A.2. European exploration routes by Robinson (1927)

Notes: This map shows the European explorations routes as drawn by Robinson (1927).

Table A.5. Alternative sources

	Dependent Variable: Binary variable for night light					
	(1) HMI & RA	(2) DIG & RA	(3) DIG	(4) HMI=HMI & RA	(5) HMI=DIG & RA	(6) HMI=DIG
Trade Routes	0.012***	0.012***	0.011***	0.049***	0.049***	0.051***
	(0.002)	(0.003)	(0.003)	(0.008)	(0.008)	(0.008)
Local Gov FE	✓	✓	✓	✓	✓	✓
Geo & Hist Controls	✓	✓	✓	✓	✓	✓
N	79731	79731	79731	59266	62922	62323
R^2	0.232	0.232	0.232	0.223	0.218	0.217

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight,and 0 otherwise. This variable uses data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. Columns (1)-(3), Trade Routes is a measure of Aboriginal trade routes. In columns (1)-(3), trade routes were created based on a variety of sources. In column (1), the variable uses a weighted least-cost algorithm based on the Human Mobility Index (HMI) from Özak (2018) and data on the location of Aboriginal rock art. In column (2), a weighted least-cost algorithm based on historical maps from Mc̈Carthy (1939) and the location of Aboriginal petroglyphs is used. In column (3), the variable uses a weighted least-cost algorithm based only on the historical maps of Mc̈Carthy (1939). Columns (4)-(6) use only cells for the OLS regressions where the measurement of pre-colonial Aboriginal trade routes based on HMI alone 'agrees' with the existence of a route. Column (4) uses a dummy variable that takes the value 1 if cell *i* hosts a trade route based on the HMI and the location of Aboriginal rock art. Column (5) uses a dummy variable that takes the value 1 if cell *i* hosts a trade route based on the historical maps of Mc̈Carthy (1939) and the location of Aboriginal rock art. Column (6) uses a dummy variable that takes the value 1 if cell *i* hosts a trade route based on the historical maps of Mc̈Carthy (1939). All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

Table A.6. Aboriginal Trade Routes, Night Lights & Population Density

Panel A:	Dependent Variable: Binary dummy for night light					
	(1) all cells	(2) excl. 50km	(3) excl. 100km	(4) excl. 200km	(5) excl. 300km	(6) excl. 500km
Trade Routes	0.030^{***}	0.024^{***}	0.021^{***}	0.018^{***}	0.015^{***}	0.007^{**}
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)
Local Gov FE	✓	✓	✓	✓	✓	✓
Geo & Hist Controls	✓	✓	✓	✓	✓	✓
N	79731	72474	65382	52803	41838	23744
R^2	0.233	0.165	0.149	0.111	0.060	0.031
Panel B:	**Dependent Variable: Population Density**					
	(1) all cells	(2) excl. 50km	(3) excl. 100km	(4) excl. 200km	(5) excl. 300km	(6) excl. 500km
Trade Routes	0.975^{***}	0.851^{***}	0.758^{***}	0.684^{***}	0.582^{***}	0.662^{***}
	(0.148)	(0.147)	(0.129)	(0.133)	(0.108)	(0.133)
Local Gov FE	✓	✓	✓	✓	✓	✓
Geo & Hist Controls	✓	✓	✓	✓	✓	✓
N	79731	72474	65382	52803	41838	23744
R^2	0.600	0.582	0.570	0.528	0.476	0.281

Notes: The unit of observation is a grid cell of 10km X 10km. In Panel A, the dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight,and 0 otherwise. This variable uses data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. In Panel B, the dependent variable is the logarithm of human population density, which is the number of individuals per grid cell. The data is derived from national censuses and population registers for the year 2015, with an additional minor adjustment of 1e-8 included. Trade Routes is a dummy variable that takes the value of 1 if cell *i* has at least one Aboriginal trade route, and 0 otherwise. In column (1), all grid cells in the sample are used. From columns (2)-(6), cells are progressively excluded that are 50km (col. 2), 100km (col 3), 200km (col 4), 300km (col 5) and 500km (col 6) close to the shoreline. All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

Table A.7. Network analysis

	Dependent Variable: Binary variable for night light					
	(1)	(2)	(3)	(4)	(5)	(6)
Trade Routes	0.027***	0.029***	0.030***	0.030***	0.030***	0.023***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Centrality: Mean Degree	1.023***					
	(0.204)					
Centrality: Mean Betweenness		1.044***				
		(0.197)				
Centrality: Mean Eigenvector			1.423***			
			(0.270)			
Centrality: K-B(b=1)				1.423***		
				(0.270)		
Centrality: K-B(b=0)					1.423***	
					(0.270)	
Centrality: K-B(b=0.5)						0.180***
						(0.022)
Local Gov FE	✓	✓	✓	✓	✓	✓
Geo & Hist Controls	✓	✓	✓	✓	✓	✓
N	79731	79731	79731	79731	79731	79731
R^2	0.234	0.234	0.233	0.233	0.233	0.235

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight,and 0 otherwise. This variable uses data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. Degree, betweenness, eigenvector and Katz-Bonacich (K-B) centrality measures are straightforward applications to weighted networks of the respective concepts (Bloch *et al.* (2021)]. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

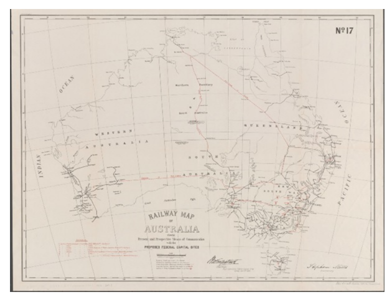
Table A.8. Excluding starting & destination points

	Dependent Variable: Binary variable for night light	
	(1)	(2)
Trade Routes	0.024***	0.016***
	(0.005)	(0.005)
Local Gov FE	✓	✓
Geo & Hist Controls	✓	✓
N	79425	72495
R^2	0.229	0.203

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight,and 0 otherwise. This variable uses data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. In column (1), cells associated with a starting and destinations were excluded. In column (2), buffers of 50km around starting and destinations were created and consequently all cells within these buffers were excluded. All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

(a) 1880

(b) 1890



(c) 1900

(d) 1920

Figure A.3. Maps of the railway network in Australia between 1880-1920.

Notes: This figure shows the development of railway infrastructure in Australia between 1880 and 1920.

Table A.9. Excluding Australian States

	Dependent Variable: Binary variable for night light					
	(1) Western Australia	(2) Northern Territory	(3) South Australia	(4) Queensland	(5) Victoria	(6) New South Wales
Trade Routes	0.030***	0.031***	0.031***	0.030***	0.030***	0.030***
	(0.006)	(0.006)	(0.005)	(0.007)	(0.005)	(0.006)
Local Gov FE	✓	✓	✓	✓	✓	✓
Geo & Hist Controls	✓	✓	✓	✓	✓	✓
N	50776	65959	69826	62758	77547	71789
R^2	0.260	0.243	0.229	0.241	0.202	0.222

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight,and 0 otherwise. This variable uses data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. In column (1), cells associated with the state of Western Australia were excluded. In column (2), cells associated with the state of Northern Territory were omitted. In column (3), cells linked to the state of South Australia were dropped. In column (4), cells linked to the state of Queensland were excluded. In column (5), cells corresponding to the state of Victoria were dropped. In column (6), cells corresponding to the state of New South Wales were omitted. All columns control for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

Table A.10. Spatial Autocorrelation

	Dependent Variable: Binary variable for night light
	(1)
Trade Routes	0.030**
	(0.004)
Local Gov FE	✓
Geo & Hist Controls	✓
N	79731
R^2	0.233

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight,and 0 otherwise. This variable uses data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. Column (1) controls for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

Figure A.4. Highway network in Australia by 1950

Notes: This map shows the Highway network in Australia by 1950

Table A.11. Omitted Variable Bias (Oster's test)

	Dependent Variable: Binary variable for night light			
	(1) Baseline specification coefficient $\dot{b}$	(2) Identified Set ($\dot{b}$(Rmax,Delta=1),b)	(3) Exclude Zero	(4) Absolute Delta (δ)
Trade Routes	0.030	$[0.028, 0.030]$	✓	$6.6 > 1$
Local Gov FE	✓	✓		
Geo & Hist Controls	✓	✓		
N	79731	79731		

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell i has nightlight,and 0 otherwise. This variable uses data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. In column (1), the conservative coefficient is given. Column (2) shows the range of coefficients between the conservative estimate (b) and the new b coefficient ($\dot{b}$(Rmax,Delta=1)) obtained on the basis of the technique proposed by Oster (2019). In column (3), ✓indicates that ($\dot{b}$(Rmax,Delta=1),b) safely excludes zero, indicating that omitted variable bias is ruled out. In column (4), 10.3 ¿ 1 means that the parameter δ exceeds one, indicating that the model from equation 1 is most likely not affected by omitted variable bias. The regression controls for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical, climatic, and historical variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

Table A.12. Omitted Variable Bias (Spatial First Differences)

	Dependent Variable: Binary variable for night light	
	(1) West-East direction	(2) North-South direction
Trade Routes (Differences)	0.021***	0.02***
	(0.003)	(0.003)
Bootstraped t-statistic	[3.99]	[3.96]
N	79730	79730

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight,and 0 otherwise. This variable uses data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. In column (1), the estimate calculates spatial first differences (SFD) in the west-east direction as proposed by Druckenmiller and Hsiang, 2018, while in column (2) this is calculated for the north-south directions. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

B. Coastal Trade Dynamics

While the main analysis has excluded the first layer of coastal grid cells due to data limitations, coastal trade may still have played an important role in shaping modern economic activity and urbanisation patterns in Australia. Therefore, we address this issue in three ways.

First, we construct a measure based on recorded shipwrecks along the Australian coastline, which serves as a proxy for coastal trade. More specifically, we work with the Australian National Shipwrecks database (*Geospatial Data* n.d.) and count the number of shipwrecks from 1622 to 1900 within a 50-kilometer radius encircling each coastal cell. Then, within our dataset comprising non-coastal cells, we measure the distance of each cell to its nearest coastal counterpart, and assign to it its inverse so that cells that are closer to the coast are assigned a higher weight. We then associate with each observation a magnitude which is the product of the inverted distance and the number of shipwrecks. Column 1 of Table A.13 reports a coefficient on the number of historical shipwrecks, thus adjusted and referred to as Coastal Trade, which is positive and significant. Notably, the coefficient of our main variable of interest, Trade Routes, remains positive and significant.

Second, we utilise data from Bakker et al. (2021) who define a connectedness variable – a coastal indicator for pre-industrial trading opportunities based on the shape of the shoreline. We calculate the average connectedness for each coastal cell within a circular buffer of a 50km radius, and we repeat the same process with the inverse distances as we describe above. That is, as we move further into the interior of Australia, the cells are assigned smaller weights. Then, each

Table A.13. Coastal Trade Dynamics

	Dependent Variable: Binary variable for night light			
	(1)	(2)	(3)	(4)
Trade Routes	0.031***	0.029***	0.026***	0.026***
	(0.005)	(0.005)	(0.005)	(0.005)
Coastal Trade	0.028***			0.021***
	(0.006)			(0.005)
Connectedness		−0.007**		0.001
		(0.003)		(0.002)
Local Gov FE	✓	✓	✓	✓
Longitude FE			✓	✓
Longitude FE X Dist. to Sea			✓	✓
N	79731	78238	79731	78238
R^2	0.234	0.231	0.251	0.253

Notes: The unit of observation is a grid cell of 10km X 10km. The dependent variable is a dummy variable that takes the value of 1 if cell *i* has nightlight, and 0 otherwise. This variable uses data from Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. Trade Routes is a dummy variable that takes the value of 1 if cell *i* has at least one Aboriginal trade route, and 0 otherwise. All columns control for local government fixed effects. In column (1) Coastal Trade is variable measuring coastal trade intensity. In column (2), Connectedness measures the mean connectedness of the closest coastal cell within 50km. In column (3) and (4), it is added longitude fixed effects and the interaction between longitude fixed effects and proximity to coast. All regressions controls for local government fixed effects, as well as for a set of geographical, climatic and historical variables, which include: the coordinates of each grid cell, agricultural suitability, elevation, ruggedness (standard deviation of elevation), rainfall and standard deviation of rainfall, temperature and standard deviation of temperature, distance to the sea, distance to Sydney, distance the state capital, distance to historical mines, coastal presence, and water percentage. The descriptions of the geographical and climatic variables can be found in the Appendix. Robust standard errors clustered at the local government district level were used and the constant term was omitted for space. *, ** and *** mean that the coefficient is statistically significant at 10%, 5% and 1% respectively.

cell gets a value which is the multiplication of its weight and the average connectedness of its closest coastal cell.[23] Column 2 of Table A.13 shows that the coefficient on connectedness is negative and significant. This may suggest that contemporary economic development in Australia has not been influenced significantly by the coastal trade activities, perhaps because of the landscape. Indeed, the northern part of the country, which benefits from greater geographical connectivity to Polynesia and Asia via the sea, has not necessarily experienced markedly greater development compared to the southern part. The latter hosts prominent urban centers, such as Sydney and Melbourne.

Third, in column 3 of Table A.13, we control for longitude fixed effects coupled with their interaction with proximity to the sea. These controls aim at reducing the risk of confounding effects stemming from location-specific variables that are constant over time within each longitude and for potential influence of coastal areas on trade patterns and economic opportunities as one moves closer or farther from the coast. The coefficient on Aboriginal trade routes remains unchallenged. Lastly, in column 4 of Table A.13, we add together all controls of coastal trade along with longitude fixed effects and their interaction with proximity to the sea. Nevertheless, the coefficient of Aboriginal trade routes re-

[23]We lose 1,493 observations by creating this control due to the fact that the closest coastal cells have missing values of connectedness within a circular buffer of a 50km radius.

mains unaffected while the effect of connectedness not only is reversed but also becomes insignificant. This underscores the robustness of our findings and reinforces the notion that Aboriginal trade routes continue to exert a significant impact on contemporary economic activity in Australia, irrespective of coastal trade dynamics.

C. Variable definitions

Table B.1. Variable definitions and sources

Variable	Description	Source
Main variables		
Trade routes	Cost-effective routes between origins and destinations using (weighted) least-cost path analysis.	Authors' elaboration from McCarthy (1939)'s historical descriptions and the Human Mobility Index (HMI) as a cost weight drawn from Özak (2018).
Night light	Dummy variable showing if there is light within a cell.	Authors' elaboration using VIIRS's lights in 2015 from Elvidge et al. (2017) and NOOA/National Centers for Environmental information: here
Latitude/Longitude	Geographic coordinates of the cell.	Authors' elaboration using ArcGIS.
Agriculture Suitability	Average value of seven key soil dimensions important for crop production: nutrient availability, nutrient retention capacity, rooting conditions, oxygen availability to roots, excess salts, toxicities, and work-ability. It corresponds to the average value of the surface area of the cell.	Authors' elaboration using data from Fischer et al. (2008): here
Elevation	Average altitude in meters above or below the sea level. It corresponds to the average value of the surface area of the cell.	Author's elaboration using data from DIVA-GIS.
Ruggedness	Standard deviation of the altitude (in meters above or below the sea level) of the territory corresponding to the cell.	Author's elaboration using data from DIVA-GIS.
Precipitation and (StDev Precipitation)	Mean and (standard deviation) of annual precipitation, in millimeters. They correspond to the average value of the surface area of the cell.	Author's elaboration using data from WorldClim by Hijmans et al. (2005).
Temperature and (StDev Temperature)	Annual average and (standard deviation) of temperature, in degrees of Celsius. It corresponds to the average value of the surface area of the cell.	Author's elaboration using data from WorldClim by Hijmans et al. (2005).
Distance to the Sea	The geodesic distance from the centroid of each cell to the nearest coastline, in kilometres.	Authors' elaboration using ArcGIS.
Coastal Dummy	Dummy showing whether cells face a coast using the second layer of coastal cells.	Authors' elaboration using ArcGIS.
Distance to Sydney	The geodesic distance from the centroid of each cell to Sydney, in kilometres.	Authors' elaboration using ArcGIS.
Distance to State Capital	The geodesic distance from the centroids of the cells of each State to their corresponding State capital, in kilometres.	Authors' elaboration using ArcGIS.
Distance to Historical Mine	The geodesic distance from the centroids of the cells to the closest historical mine, in kilometres.	Author's elaboration using data from the Australian mining history association: here
Water Percentage	Percentage of water due to rivers, canals, and lakes of the cell.	Author's elaboration using DIVA-GIS.
Other variables		
Early Railways	Dummy variable showing whether there is an early railway in the cell.	Author's elaboration digitising historical maps of railways. See Figure A.3 in the Appendix.
Early Highways	Dummy variable showing whether there is an early highway in the cell.	Author's elaboration digitising a historical map of the highway network in 1950. See Figure A.4 in the Appendix.
Early Explorations	Dummy variable showing whether there is an early exploration route in the cell.	Author's elaboration digitising a historical map by Robinson (1927). See Figure A.2 in the Appendix.
Cities 1788-2000	The foundation year of the most populated cities (that cover almost 90% of the population) in Australia.	Data from Kampanelis (2019).
Population density	Logarithm of human population density (number of persons per grid cell) based on counts consistent with national censuses and population registers for 2015 plus a tiny number (1e-8).	Author's elaboration using population density data from Global Human Settlement Layer (GHSL): here. European Commission (2023).
Primary Roads	Main roads in Australia as defined by DIVA-GIS dataset.	Author's elaboration using DIVA-GIS.
Centralities	Authors' computations based on historical descriptions and the Human Mobility Index (HMI) as a cost weight drawn from Özak (2018).	See definitions for degree, betweenness, eigenvector and K-B centralities in 3.5.4
Trading Sites	A dummy variable that takes the value of 1, if at least one Aboriginal trading point (origins and destinations) is present in each cell, and 0 otherwise.	Authors' elaboration from McCarthy (1939)'s historical descriptions.
Alternative sources	Cost-effective routes constructed based on origins and destinations drawn from McCarthy (1939), rock art locations, and historical maps of McCarthy (1939). The routes then rely on a (weighted) least-cost path analysis.	Authors' elaboration from McCarthy (1939)'s historical descriptions, Human Mobility Index (HMI) by Özak (2018), rock art locations drawn from the Centre for Rock Art Research and Management here, and McCarthy (1939)'s maps.
Natural Routes	The variable "Natural Routes" measures the traversability of locations in Australia based on geographically intrinsic routes. It quantifies the number of optimal travel paths intersecting each pixel on a 10 km x 10 km map, with higher scores indicating better Natural Routes.	Authors' computations based on the Human Mobility Index (HMI) as a cost weight drawn from Özak (2018), using ArcGIS.
Coastal Trade	The multiplication of the number of shipwrecks between 1622 and 1900 and the inverted distance related to the closest coastal cell. Further explanation in Section B of Appendix.	Authors' elaboration using data from the Australian National Shipwrecks database: here
Connectedness	The mean connectedness of the closest coastal cell within 50km.	Authors' elaboration using data from Bakker et al. (2021)