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Abstract

This study examines how the historical rail stations condition long-run development, using Colonial Malaya as a laboratory. Constructing a novel historical data on rail stations, agglomeration centers, tin mines and rubber plantations dated back to a century and matching with contemporary data on economic activity at one-kilometer cell level, we find that the earlier a region obtains rail stations, the higher level of economic activity it performs today due to agglomeration economies. These results hold even in regions that have already abandoned colonial stations. This study signifies the role of investment on transport infrastructure to accelerate local economic activity.

1. Introduction

Railroad infrastructure supports the engine of economic development. Rail is the most efficient transportation mode; it literally geared the industrial revolution in the eighteenth century.[1] Krugman (1991b) argued that an efficient transportation network reduces transportation and trade costs, creates increasing returns to scale, boosts the marginal productivity of private inputs, and eventually triggers economic activity. While most developed countries rely on railroads for transporting freight and moving masses, developing countries are yet to reap the potential benefits of rail networks. For instance, many colonial countries failed to extend their railroad network after declaring independence. British India built 67,247 km in rail lines from 1853 to 1930, and these were expanded by only around 1.78% in the past 90 years. Such a negligence is partly due to the countries' lack of capital, but mostly due to their policy biases toward road infrastructure.[2] In this context, we lack rigorous empirical evidence to inform public policy on how railroad infrastructure boosts economic activity through the agglomeration of firms around railroad stations in the long term.

In this paper, we exploit one of history's natural experiments: the colonial network of railroads and its associated railroad stations in colonial Malaya.[3] While the construction of railroads in British colonies was commonplace, it is somewhat surprising that Malaysia did

[1]By 1847, many industrialized countries such as the United States (13,500 km), Great Britain (9,800 km), Germany (5,800 km) and France (2,900 km) had built extensive railroad networks (see Büchel and Kyburz (2018)).

[2]In 2017, almost 18 percent of World Bank lending was allocated to transportation infrastructure projects, almost the same share as that of education, health, and social services combined (World Bank, 2019).

[3]In this paper, we interchangeably use "Malaysia" as "Peninsular Malaysia" that was the former colonial "Malaya".

not expand its 1,900 km of railroads built during the colonial period (i.e., 1885–1931) until 1995. Recently, Malaysia has planned to roll out two big-ticket transportation infrastructure projects—the East Coast Rail Link and National Fiberisation and Connectivity Plan. No causal study has hitherto pursued the true impact of such mega-projects on economic activity in the long term.[4] Malaysia offers an ideal context for us to address this gap by examining whether railroads built a century ago have any effect on economic performance today.[5]

This paper makes three contributions to our understanding of railroad infrastructure projects. First, we depart from the extant literature by focusing on railroad *stations* in addition to railway lines using highly detailed cell-level data from colonial Malaya.[6] A potential reason that none has studied the bearing of historical railroad stations is the dearth of data. Remarkably, colonial Malaya maintained detailed records of its railroad stations; however, such records have never been systematically digitized for research. We construct a novel dataset on the historical railroad network during 1885–1931, containing 107,072 cells at roughly a 1×1 km level covering the whole of Peninsular Malaysia.[7] Besides, we merge our

[4]We understand rather little about the impact of transportation infrastructure on countries in South East Asia such as Malaysia. Most studies focused mainly on developed countries (United States by Atack et al. (2010); Prussia by Hornung (2015); and Switzerland by Büchel and Kyburz (2018)); some emphasised on developing countries (China by Banerjee et al. (2020); India by Donaldson (2018); Ghana by Jedwab and Moradi (2016); and Kenya by Jedwab et al. (2017)).

[5]This approach shields our estimations from biases related to reverse causality. Similar approach has been adopted by Jedwab and Moradi (2016), Jedwab et al. (2017) and Okoye et al. (2019).

[6]Railway lines might capture dubious effect, as railway lines are useless unless the locals get access to its service. The causal inference about the importance of railroad network can be ascertained more precisely by examining the effect of railroad stations on its local economic activity. Therefore, the findings of existing studies are somewhat downward biased, as data on railway stations are embedded into their data on railway lines (arguably, there should be at least one railroad stations located in each city or locality).

[7]We constructed a comprehensive network of historical railroad stations in Malaysia by com-

stations network data with the night lights satellite data sourced from the United States Air Force Defense Meteorological Satellite Program (DMSP) as an indicator of current local economic activity, making it highly likely to capture the net economic effect of railroads. Our results are also robust to a harmonised night lights data generated by Li et al. (2020) accounting for the newer night lights data from the Visible Infrared Imaging Radiometer (VIIRS).[8] No paper has hitherto examined the effect of railroad stations on today's economic performance at such a fine geographic level.[9] Our result indicates that railroad stations boosts economic activity in the long run.

Second, this paper makes progress in understanding the rise of *agglomeration* economies as the underlying mechanism through which historical railroad stations stimulate current economic activity. We geo-reference the locations of all economic growth centers (i.e., agglomeration centers) of 1922 and 1967 in Malaysia. Using a two-stage least-square instrumental variable (2SLS-IV) approach, we find that the emergence of new agglomeration centers (villages, towns, district headquarters, state capital) is conditional on the access to railroad stations. In particular, our estimates indicate that railroad stations facilitate agglomeration centers, which in turn stimulate economic activity to the present. In addition, we take our analyses further to understand whether railroad stations trigger agglomeration through firms or population. In doing so, we overlay railroad stations on the spatial distribution of

piling data extracted from various government repositories, historical reports and railroad maps (see Appendix A1 that provides a full account of our data sources). We validated the accuracy of our dataset with Google earth map and cross-checked the georeferencing of railroad stations for gaining precision.

[8]See Gibson (2021) and Gibson et al. (2021) for a detailed explanation and comparison between data from both sources.

[9]Storeygard (2016) used the satellite data on lights at night as a proxy for economic activity, and new road network data to calculate the shortest route between cities. Our work is different in that we link the night-lights data with the historical railroads network data to estimate its impact on current economic activity. Similarly, Jedwab and Moradi (2016) used the satellite-based night lights data in their auxiliary analyses.

firms and population. We find that colonial railroad stations induce contemporary economic activity through the agglomeration of firms and population.[10] Overall, our finding indicates that railroad infrastructure acts as a center of agglomeration economies, which corroborates the celebrated Marshall (1920) theory of agglomeration; firms and labor will conglomerate (around railroad stations) to reduce transport costs.

Third, we investigate how local economic activity around railroad stations propagates through spatial distances—a *spillover* effect—that is crucial to rule out endogeneity in our estimation model. Particularly, we horizontally shift our "treatment cell" of analysis away from actual railroad stations to estimate whether the rail network affects distant areas. We find evidence that the economic effects of railroads concentrate around the stations and such effects propagate spatially at a diminishing rate. This finding concurs with that of Rosenthal and Strange (2003). In particular, the agglomeration of firms occurs within the 1 km range of railroad stations, but its spillover effect reaches as far as 10 km away.

A natural concern when estimating the persistent impact of historical railroad stations on current economic activity is whether the construction of railroads was endogenous to "location bias" (see Fishlow (1965); Büchel and Kyburz (2018)). That is, the underlying challenge is to confirm whether the railroad network enabled the generation of economic activity in the century, or whether the network was the result of pre-existing economic characteristics related to associated locations. The latter case would exacerbate endogeneity concerns because the decision to set a railroad station in a particular location depended on observable and unobservable factors correlated with population growth (see Büchel and Kyburz (2018); Asher and Novosad (2020)). We tackle this challenge in three ways. First, unlike the extant literature, we measure the impact of railroad stations on economic activity at a 1×1 km

[10]This approach is quite important as it shields omitted variables biases into our estimation framework.

cell level, meaning that we compare the current economic activity in the cells with railroad stations and associated neighboring areas within 1 km. Since the pre-existing characteristics such as geographical, cultural, economic or political differences were unlikely to vary between the areas with railroad stations and its adjacent locations, our findings drawn from the 1 km cell-level analysis are immune from such endogeneity.[11] Second, the pre-existing economic characteristics are presumably limited in the colonial Malayan context because the British government built railroad stations to move either tin or rubber to ports. The construction of railroad stations was not conditional on local population growth; the colonial government operated its tin extraction and rubber cultivation activity using migrant workers from nearby overpopulated countries (e.g., India and China). Hence, we adopt a formal estimation approach in which we explicitly control for tin mining sites and rubber cultivation areas to further minimize endogeneity concerns related to pre-existing economic characteristics. Third, we restrict our estimates with an additional control that measures the shortest spatial distance between each station and the nearest straight-line path between major stations. Assuming that each rail line is likely to connect two primary stations—that were near to tin mining or rubber cultivation sites—through its linear (i.e., nearest) path to minimize construction costs, this additional control allows us to account for location bias related to secondary stations that were between two primary stations (deviated from the linear line).

Several potential concerns when estimating any spatial impact of infrastructure projects include biases related to migration. We address "migration bias" in our estimates using historical population census data on migration. Historically, the British government recruited Chinese and Indian people to work in tin mining or rubber plantation sites. Because railroad

[11]In addition to the cell approach, we adopt a ring approach where we draw circles with varying length of radii using rail stations as center points; the circles are considered as treatment and the outer areas as control.

stations were built around such sites, it might be possible to capture the effect of induced immigrant workers under the mask of railroad stations. We confine such confounding factors by controlling for historical Chinese and Indian population. Further, we mitigate other omitted variable biases following Oster (2019), guaranteeing that our estimates are not an artifact of unobservable factors.

Our paper relates to literature that explores the agglomeration effects of railroad stations.[12] Krugman (1991b) indicated that large-scale agglomerations may emerge from the interaction of "increasing returns to scale" and the decrease in transport costs in the presence of firms and productive factors mobility. Similarly, Hanson (1997) specified that a small-scale concentration of firms attracts consumers and workers to a particular area; such a population increase creates a larger market that gradually facilitates a large-scale agglomeration of firms, generating the so-called "home market effect". Another notable work is that of Duranton and Puga (2004), who identified three mechanisms—sharing the common infrastructure (e.g., railroads), matching between employers and employees (i.e., labor pooling), and learning between people (e.g., technology transfer)—through which agglomeration is fostered. We argue that the railroad network reduces transport costs, incentivizing private investors and workers to co-locate near railroad stations. Our analyses, using both "cell" and "ring" approaches, suggest that the agglomeration effect is strongest at the local level and the effect is attenuated quickly with distance to the railroad stations. In addition to this agglomeration effect, we shed light on the spillover effects by horizontally shifting our "cell" of analysis away from the railroad stations. We find evidence of the decreasing effect of railroad stations in space; such an effect disappears in areas 10 km away from stations. This result is consistent with Myrdal and Sitohang (1957) "backwash effect," in that the *lucky* areas with railroad stations will attract economic resources away from the *unlucky*

[12] See Rosenthal and Strange (2004) for a survey on the nature and sources of agglomeration economies.

ones, especially via migration, capital movement, and trade. We also rationalize this finding in the spirit of a trade-off between agglomeration benefits and congestion costs—some firms are better served locating in a denser area, while others prefer to locate in a more disperse area (Rosenthal and Strange, 2003). Overall, our study provides evidence on whether and to what extent railroad stations trigger the agglomeration and spillovers of economic activity across space.

Our paper adds to a rich body of literature on the impact of railroad infrastructure on economic activity. The economic impact of railroads in nineteenth-century United States (US) has been studied extensively, led by Fogel (1964) and Fishlow (1965). More recently, with the advent of technology and geographic information—processing platforms (e.g., ArcGIS), a growing body of research has examined the causal relationship between transportation infrastructure and economic growth.[13] Jedwab and Moradi (2016), Jedwab et al. (2017), and Okoye et al. (2019) investigated the long-term impact of colonial railroads built by the British colonies in African countries.[14] These studies supported the "path dependence hypothesis," arguing that localized historical shocks (e.g., the construction of colonial railroads) can have a persistent impact on the distribution of economic activity to the present.[15] Our paper moves beyond this strand of research in two important ways. First, our study pins down the role of private-sector investment in firms as a potential mechanism through which railroad stations affect the spatial distribution of economic activity. Identification of such a mechanism is rare in the extant literature. Second, our evidence for path dependence

[13]See Redding and Turner (2015) for a review of this literature.

[14]Other studies looking into the long-term impact of railroads include Berger and Enflo (2017) focusing on urban growth in Sweden, Hodgson (2018) examined the persistent impact in American West while Banerjee et al. (2020) looked into the long-term economic outcome in China. All three studies provided evidence of long-term economic impact in areas located near to the historical railroads.

[15]In a similar vein, Bleakley and Lin (2012) argued that cities persist in former portage sites even if no natural advantages exist to the present.

in the development process in Malaysia contributes to the growing literature on long-term economic development. Extant literature has mostly studied the medium-term (0–40 years) effects of railroad infrastructure.[16] Conversely, our focus on colonial railroad stations in the longer term (0–130 years) enriches our understanding of the economic effects of both colonial legacy and railroad stations on its vicinities.[17] We categorically identify colonial railroad stations that were either abandoned permanently or closed temporarily because of destruction during the Japanese strategic bombing operations and their subsequent reconstruction efforts. Such a historical context is critical; it allows us to identify the causal inference on the time persistence of economic activity associated with the railroad network. Our results echo those of Jedwab and Moradi (2016) and Okoye et al. (2019), and support the path-dependence theory—colonial railroad stations have enduring effects on the spatial distribution of economic activity.

Lastly, our paper also contributes to the literature on long term impact of colonial investment. For instance, Huillery (2009) finds that colonial investments in health, education and infrastructure are a strong determinant of current development in West Africa. Dell and Olken (2019) show that despite its extractive nature and motive, areas close to Dutch established sugar factories in Java are more industrialised today. Similarly in our context, rail networks built by the British are extractive in nature as their main motive was to extract natural resources. Nevertheless, our results echo those from the literature, areas with

[16]Most previous studies focused on the railroad impact in the short to medium term. For example, Atack et al. (2010) investigated the impact of railroad access on human settlement pattern in American Midwest between 1850 and 1860 while Hornung (2015) examined the impact of railroad access on population growth in Prussia during the period of 1840 to 1871.

[17]Berger and Enflo (2017) estimated the impact of railroads on urban growth in Sweden from 1855 to 2010, while Hodgson (2018) examined the impact of railroad built between 1868 and 1899 on the distribution of towns in 2010. On the investigation of the persistent impact of colonial railroad, Jedwab and Moradi (2016) and Okoye et al. (2019) focused on a period of 110 years in the context of African countries.

colonial rail stations have a higher economic activity today.

The remaining of the paper is organized as follows. Section 2 explains the historical background of railroad development in Malaysia. Section 3 describes the source of data with some summary statistics. Sections 4 present the empirical strategy and explain strategies used in identifying causal relationships. Section 5 reports our estimation results, and Section 6 concludes.

2. Historical Background

Railroad development in Peninsular Malaysia can be separated into three main phases under the era of British colonization (Kaur, 1980a). The first phase (1885–1896) concentration on the west coast of Peninsular Malaysia to serve the tin mining industry. It consists of four major lines as shown in Appendix A2 (Fisher, 1948). All four lines were constructed to connect the inland tin-mining area to the nearest coastal port (Kaur, 1980b). Most of these initial lines have been abandoned now except railroad lines that connecting Klang to Kuala Lumpur, and Ipoh to Batu Gajah.

The second phase (1897–1909) is an extension of the existing railroads. Its construction connect the major cities on the west coast to the existing lines to further facilitate transporting tin ore to the nearest coastal port. The lines were mainly longitudinal, connecting from south to north. Pahang is the only state under British controlled during that period yet to be connected by the end of the second phase. Several attempts to expand railroad into Pahang but failed mainly due to its rough topography issues (Fisher, 1948; Kaur, 1980a).

The third phase (1910–1931) connects northern states and the east coast to meet the rubber plantation needs. In the early twentieth century, rubber became an important commercial commodity. Over time, rubber cultivation area expanded from 2,190 square kilometres (km^2) in 1910 to 13,860 km^2 in 1940 (Lees, 2017). As such, it is suggestive that railroads inspired colonial Malaya to transform into an export-oriented economy, massively specialized in tin and rubber. Since Pahang is located in the middle of the west and east coast, railroad lines must extended through Pahang before extension to Kelantan from the west coast. The railroad network to the east coast was fully completed in 1931.

No railroad lines have been extended until 1995. Nonetheless, several colonial railroad stations were abandoned, and some were destroyed during the Japanese strategic bombing operation in the 1940s. Figure 1 shows the railroad network in Peninsular Malaysia.

3. Data and Measurement

3.1. Rail Lines and Stations

We construct a dataset that consists of 107,072 cells of 0.01×0.01 decimal degrees (roughly 1 km^2), covering the whole of Peninsular Malaysia. Rail lines and station data were collected and compiled from various sources.[18] A validation exercise is carried out to cross-check the location of all railroad stations with the recent Google Earth map. Several historical rail lines and stations in East Malaysia are excluded from the analysis due to data unavailability.

We rely on a binary indicator that takes the value of 1 if one or more railroad stations are located in a particular cell.[19] As such, our treatment group consists of cells with at least

[18]See Appendix A1 for the list of data sources.

[19]The cell is considered to have railroad access if the railroad station have ever been constructed in that cell even though were later abandoned.

one historical railroad station while our comparison group is cells without railroad stations. Our data only limits to railroad stations built before 1931 as that is the end of the major railroad construction and there is no additional railroad network development until 1995. In total, we identified 307 colonial railroad stations built during 1885–1931.

3.2. Night Lights Data

Following most literature, we adopt the geo-coded night lights intensity data as an indicator for economic and human activity.[20] These lights are satellite images composed by the Operational Linescan System sensors installed on satellites of the United States Air Force Defense Meteorological Satellite Program (DMSP). The raw dataset is then being processed to remove lights from sunlight, moonlight, aurorae, forest fire, and cloud to capture only the man-made lights. The night lights intensity in each cell is depicted by the digital number (DN) ranging from 0 to 63, where 0 indicates no lights while 63 is the maximum brightness level. We rely on the average visible DN of cloud-free light detections multiplied by the percent frequency of light detection to capture the amount of time for each light detection. If the light is only detected half of the time, the value will be discounted by 50 percent.

We use night lights intensity between the years 1992 and 1994 as our dependent variable to measure economic activity level. These years were chosen because night lights data are available starting in 1992 while the modern railroad connections were built in 1995. The modern railroads were constructed to enhance connectivity between major cities surrounding

[20]Henderson et al. (2012) and Chen and Nordhaus (2011) justified that night lights intensity is a reliable proxy for economic growth. They found that the annual variations in Gross Domestic Product (GDP) are highly correlated with the changes of night lights intensity. Hu and Yao (2019) argued that using GDP per capita to proxy for economic development are less accurate for low- and middle-income countries and night lights can be used to improve the aforesaid measure.

the capital city of Kuala Lumpur. We could reasonably expect that the modern railroads may affect the economic growth pattern from 1995 onwards and excluding these modern railroads may surmount the endogeneity concern.

3.3. Other Variables

We incorporate various controls in our analysis to account for any potential contaminating factors. These control variables include (i) tin mining areas to account for local geographical endowment, (ii) rubber cultivation areas similarly, to take into account of pre-existing endowment (iii) major rivers to control for an alternative mode of transport, (iv) topography ruggedness that may affect the construction of railroad, (v) coastal area accounting for potential transport and resource advantage gained from the ocean, and (vi) state dummy to account for the different historical institutions and economic development between states.[21]

Tin mining areas were georeferenced from the historical map at the year 1891, the earliest possible date we could obtain. We ruminate on any area within 20 km of the tin mining spot from the map as tin mining area. By considering factors such as tin mining surrounding spots, abandoned tin mining area, railroad network, topography, and maps at later period, including area within 20 km in our estimation is reasonable. Rubber cultivation areas were georeferenced from historical map at the year 1940 by Lees (2017), measured in square kilometers.

[21] See Appendix A1 that provides a full account of data sources.

3.4. Descriptive Statistics

Table 1 presents the mean of our variables of interest. Column 1 of Table 1 shows that cells with railroad station access, on average, have night lights intensity of 17.736 DN between 1992–1994, however, it is only 2.499 DN in cells without station access, as shown in column 2, suggesting positive relationship between both variables.[22] Exploring the difference between states, we find that cells without railroad stations in Penang have a DN value of 22.491, which is much larger than all other states (except Selangor), regardless of whether with or without railroad station. The large difference of night lights intensity across states suggests that the effect from railroad stations are heterogeneous across different regions and hence, provide the rationale of including state dummy in the analysis. Table comparing night lights intensity between states can be seen in Appendix A4.

4. Empirical Strategy

We exploit time lags within a cross-section setting to examine the persistent effect of colonial railroad stations on economic development. More specifically, we investigate the impact of *historical* railroad access on the night-lights-based measure of the *current* economic activity. The Ordinary Least Square (OLS) model has the following form:

$$DN_c = \beta_0 + \beta_1 STATIONS_c + \pi' X_{c,s} + \gamma_j + \epsilon_c \tag{1}$$

where DN_c is the average night lights intensity, ranging from a value of 0 to 63, between the year 1992 to 1994 for cell c; $STATIONS_c$ is a dummy variable, showing the historical

[22]Appendix A3 presents the visual comparison between areas with and without railroad stations, showing that economic activity are mostly concentrating around rail stations.

railroad station access in cell c at state s ; $X_{c,s}$ refers to a set of covariates; γ_j to state dummy and ϵ_c is a disturbance term.

4.1. Comparing Areas *With* and *Without* Railroad Stations

Our high-resolution spatial unit of a 1×1 km cell level (i.e., Cell Approach, henceforth) allows us to compare current economic activity in cells *with* rail stations and their associated neighboring cells that are within 1 km peripheries but *without* any railroad station. Since these cells are located in close vicinities, any pre-existing factors (including geographical, cultural, or political differences) are almost identical. The only difference between these cells is the existence of railroad stations (see Figure 2 that shows the schematic of the treatment cell and its associated control cells). Hence, any difference in the intensity of night lights between these adjacent cells are likely attributable to the difference in accessibility to railroad stations. By doing this, our findings drawn from 1 km cell-level analyses are likely to represent the causal impact of historical stations on economic activity to the present.

4.2. Accounting for Location and Migration Biases

The colonial British rulers constructed railroad network in places that enabled the expropriation of "tin" in the first and second phases, and "rubber" in the third phase. It tends to impose "location bias" into our estimations. We control for tin mining areas in 1891 to account for the initial local endowments that determined the location choice of constructing railroad networks. Similarly, we geo-referenced the 1940 rubber cultivation areas of 19,000 km^2 and include them in our estimation models. Thus, by controlling for both the tin mining sites and the rubber cultivation areas, we minimize "location bias" of pre-existing endowments that may contaminate our estimation setting. Besides, there could be other unobserved spatial factors such as topographic barriers, political pressures (e.g., pork barreling), and more importantly, extractive spatial choice of the colonial rulers that may seriously plague our estimation with endogenous location choices. Following Atack et al. (2010), Hornung (2015), Jedwab and Moradi (2016), and Berger and Enflo (2017), we further tackle "location bias" by augmenting our model with a control variable that measures the shortest distance from the endogenous location of *actual* to the exogenous location of *counterfactual* rail stations (see Appendix A5 that shows the locations and the creation of the straight lines). [23] Incorporating this additional control in the model accounts for the factors that deviates stations away from the respective straight lines, which further minimizes "location bias".

We are aware that our results could be subject to "migration bias", because there is a sizable influx of Chinese immigrants for tin mining and so does of Indians for rubber cultivation activities during the railroad construction period. Our results could have been driven by these mass migrations rather than railroad stations. Therefore, we include additional variables that control for the size of Chinese and Indian population in 1947.[24] Incorporating these additional controls allows us to pin down the causal effect of railroad stations on long-term economic development.

[23] Rail lines tend to be built straight (i.e., the shortest track) between two major rail stations for minimizing its construction cost, which can only deviate due to location-specific endogenous factors. Using this analogy, we define *counterfactual* rail stations that are on the straight lines but within the closest proximity of its associated *actual* stations. The straight lines and their associated rail stations are shown in Figure 1.

[24] Historical Chinese and Indian population data are obtained from historical census.

4.3. Addressing Omitted Variable Biases

Despite incorporating a set of observed covariates together with a state dummy, our estimates may still suffer from omitted unobservables that correlate with both railroad stations and economic development. Following Oster (2019), we employ an auxiliary analysis to address the concern of bias from unobservables. Oster (2019) argued that coefficient stability is insufficient to address omitted variable bias; instead, movements of both coefficients and R-squared are essential to estimate a bias-adjusted treatment effect. Hence, we employ this approach as one of our robustness checks (see Section 5.4) to mitigate the concern of "omitted variable bias".

4.4. 2SLS-IV Estimates

Our final strategy is the use of IV in explaining the causal channels between historical rail stations and current intensity of night lights. Although the latter turn out to be an ideal proxy for economic activity, it does not provide information on the mechanism through which rail stations instigate economic development. To address this concern, we approach to Krugman (1991b), which indicates that improved transportation network reduces transaction costs leading to industrial agglomeration. Hence, assuming that railroad stations affect night lights intensity through agglomeration economies, we estimate the effect of agglomeration centers on the intensity of night lights using 2SLS-IV approach.[25] By doing so, we can understand the mechanism (i.e., emergence of agglomeration centers) through which railroad stations boost economic activity.

[25]We use the geo-referenced location of agglomeration centers from 1967 historical map to apprehend the spatial distribution of economic activity.

5. Estimation Results

5.1. Persistent Impact of Historical Railroads

Using the "Cell Approach", Table 2 shows the estimates of the effect of historical rail stations on economic activity to the present using Equation (1). We report least squares estimates and robust standard errors clustered at the district level. Column 1 indicates that cells with historical rail stations, on average, have night lights intensity of 9.15 DN more than cells without rail stations, and the effect is statistically significant at the 99 percent confidence level.[26] Given the [0, 63] range of DN score, a 9.15 point night lights intensity corresponds to an increase in 14.52 percentage points (this is analogous to an increase in economic activity). This estimate will serve as our benchmark for subsequent analyses.[27]

Columns 2–4 of Table 2 test whether historical rail stations have an "accumulation effect" on economic activity over time. We do so by estimating how rail stations built in three different time periods in history (i.e., 1885–1896, 1897–1909 and 1910–1931) affect today's economic activity.[28] We hypothesize that cells that gained railroad station access earlier have

[26]Following Conley (1999), we correct for spatial correlation assuming that the spatial correlation declines linearly up to 50 km. Our result still holds as the standard error only inflated marginally and does not affect our statistical inference.

[27]As Melaka was also colonised by Portuguese and Dutch, the impact might be different from the rest of the Peninsular Malaysia due to differences in political culture. Nevertheless, dropping Melaka from the sample provides similar estimation. The result is recorded in Appendix A6.

[28]Our treatment group takes a binary dummy indicator that assigns the value of 1 if a cell obtains railroad station access during the first phase, while the comparison group takes a value of 0. Using the same approach, we create second and third phase dummies. We remove cells that gained railroad access for the other two phases from each sample to ensure our estimation reveals the effect of railroad stations in only one of the phases.

experienced greater economic development to the present. Our estimates support this notion: the coefficients for both the first and second phases are 13.8 and significantly higher than the coefficient of 5.16 in the third phase. This finding concurs with that of Berger and Enflo (2017)—i.e.,the transient shock of initial railroads induces path dependence—through which historical railroad networks have had an enduring influence on current economic activity.

We employ regional disparities to further substantiate the accumulation effect of historical railroads. In colonial Malaysia, the West Coast has gained railroad access three decades earlier than the East Coast. Our estimates in columns 5 and 6 of Table 2 show that the magnitude of the coefficient in the West Coast is larger than those in the East Coast. Such a variation can be attributed to their duration of gaining railroad access partly but not completely. Another compelling argument is that railroad network produces greater economic gains where it connects areas with ports of export. For instance, Okoye et al. (2019) reported that railroads had a sizable economic impact in the North of Nigeria, where pre-railway access to ports of export was restricted.[29] This line of argument seems plausible in our context: the West Coast railroad network of Malaysia was characterized by its interconnections with five ports including Penang, Weld, Klang (previously named as Swettenham), Dickson and Malacca, whereas the East Coast was connected with a port of Tumpat only. That is, extensive railroad connections with the Ports of export in the West Coast of Malaysia might explain its relatively higher economic gains to the present than those in the East Coast.

As a robust identification strategy, we truncate our control groups and compare the treatment cells with its eight immediate neighboring cells ("peripheral cells" henceforth) only. In this setting, endogeneity concerns related to pre-treatment conditions are further minimized, because two neighboring cells within the same vicinity are almost identical except for their

[29] Other evidence includes Hornung (2015) indicating that railroads had larger impact in the west of Prussia.

status on accessing to rail stations. The spatial diagram of the peripheral cells is provided in Figure 2. Our estimates in column 7 indicates that the economic effect of historical rail stations are substantial to the present.[30]

As most studies examine the economic impact of rail *lines* instead of rail *stations*, we run a horse-race between them. Overall, our estimates suggest that railroad stations have a higher economic impact than rail lines (see Appendix A7). One potential explanation for this larger effect could be the agglomeration and spillovers around railroad stations, which we discuss in depth in the next Section.

5.2. Agglomeration and Spillover Effects

Our estimates in section 5.1 show that railroad stations improve economic activity in 1×1 km cells with rail stations. However, as indicated by Cantos et al. (2005), transport infrastructure induces economic activity beyond its localities. This section provides insights on the extent of the long-term agglomeration and spillover effects from railroad stations.

We begin by showing how "agglomeration effect" differs from "spillover effect". In our setting, agglomeration means the tendency of economic activity to be clustered in an area while spillovers mean the tendency of economic activity to be dispersed from an area. As depicted in Figure 3, the higher night lights intensity surrounding railroad stations represents the agglomeration effect where economic activity is attracted inwards and concentrated towards rail stations to take advantage of the improved connectivity. On the contrary, the higher night lights intensity away from rail stations displays the spillover effect where economic

[30]Notice that the coefficient is relatively smaller in magnitude. This is because the peripheral cells (i.e., controls) at 1 km^2 are likely to receive economic spillovers, which make our estimates downward biased.

activity is transmitted outward. One plausible reason behind such spillovers is that some industries are better-off by locating in slightly disperse and less overcrowded areas (Rosenthal and Strange, 2003).

Using our benchmark "cell approach" framework, we now turn to estimate the agglomeration effect by expanding our initial cell size to a 0.03×0.03 decimal degree (approximately 9 km^2) and 0.05×0.05 decimal degree (approximately 25 km^2).[31] Analogous to our benchmark setting, the expanded cell will be considered the treatment group if there is at least one station located within the cell. That is, we measure the impact of railroad stations to its extended areas. The estimated coefficients are shown in columns 1–2 of Table 3. At a 1 km^2 cell level, our benchmark analysis shows our treatment cells on average have 9.15 DN higher than the comparison cells, but the effect reduces to 8.35 DN at a 9 km^2 cell level and reduce further to 6.37 at a 25 km^2 cell level. Such a declining effect indicates the presence of agglomeration economies in that night lights intensity is highly concentrated at the vicinity of rail stations.

We present our estimates in columns 3 and 4 for the samples that include the treatment along with only the peripheral cells at 9 km^2 and 25 km^2 levels, respectively. This sampling technique can potentially improve the precision of our identification strategy. Overall, this set of results provide qualitatively similar finding in that the coefficients of interest decrease as we increase the cell areas. This signifies our agglomeration economies hypothesis that areas closer to rail stations enjoy higher economic benefits.

Expanding the size of cells within our "cell approach" framework might not be an ideal method to shed light on the agglomeration effect. For instance, a rail station located at the border of a cell will only be considered to affect this cell, even if it is located next to

[31] Appendix A8 shows the diagrams for comparing the three different cell sizes.

the border of the neighboring cell (see Appendix A8). Such a case is likely to contaminate our estimates. So, as shown in Appendix A9, we propose an alternative "ring approach" in that we draw circles with varying length of radii using rail stations as center points; the circles are considered as treatment and the outer areas as control.[32] The results are shown in columns 5 and 6 of Table 3, respectively. As expected, our estimates from this "ring approach" imply that the coefficients become smaller when the size of rings gets bigger. This finding is consistent with that of "cell approach", i.e., the evidence for agglomeration economies becomes stronger in areas closer to rail stations.[33]

Our measure of average night lights intensity is rather naive especially in capturing the relative concentration of economic activity. We address this issue by constructing a night lights concentration index, which gauges how night lights concentrate in a particular cell relative to its neighboring areas.[34] The results are shown in columns 7–12 of Table 3. Our estimates provide qualitatively similar results: the relative concentration of night lights peters out as distances from rail stations increase.

Next, we attempt to understand the extent of "spillover effect" by horizontally shifting the locations of rail stations in both East and West directions at varying distances such as 3 km, 5 km, 10 km, 15 km, 20 km, and 25 km, respectively.[35] Our estimates are summarized in

[32]Consistent with the total areas of cells in our benchmark approach, the radii for treatment rings are 1.88 km for 9 km^2 level, and 3.13 km for 25 km^2 level, respectively.

[33]This finding is in line with Rosenthal and Strange (2003), in which agglomeration economies are the strongest within the first mile and diminishes quickly between 2 and 5 miles.

[34]In spirit of Riley et al. (1999) methodology, we have constructed our concentration index by calculating the square root of the sum of squared differences in night lights between a given cell and its eight immediate neighboring cells. A visual schematic of night lights concentration index is provided in Appendix A10.

[35]The construction of neighboring cells is shown in Appendix A11. The rationale for the inclusion of east and west neighboring cell is that rail lines in Malaysia are mainly longitudinal, connecting south to north. Therefore, including north and south neighboring cells might be misleading because the results not only capture the spillover effect, but also the

Table 4. Unequivocally, the coefficient falls as we move farther from the stations and become statistically insignificant once we move 15 km away from rail stations. Taking together with earlier analysis, our findings affirm that the agglomeration effect dilutes immediately after 3 kilometers (i.e., 9 km^2) while spillover effect dies out after 10 kilometers away from the stations.[36] These results also nullify that our benchmark estimates capture only lights from rail stations, as the results are still significant beyond the immediate vicinity of rail stations.

5.3. Emergence of Agglomeration Centers as a Potential Mechanism

We report that historical railroad stations stimulate economic activity in their surrounding regions, which persists even a century later. However, there is still a missing piece of the puzzle: how does historical railroad stations affect economic development to the present? We aim to unriddle one of such mechanisms by following the trail of agglomeration effect. Rail stations reduce transaction costs that may lead to the emergence of agglomeration centers (e.g., cities, towns and other economic growth hubs). Such centers may be ideal candidates for explaining economic activity to the present. To check this reasoning, we geo-referenced the location of the 1967 agglomeration centers.[37] We then constructed two measures of

direct impact of other railroad stations.

[36]Berger and Enflo (2017) and Hodgson (2018) found evidence of agglomeration shadow and reorganisation of economic activity from railroad network. That is, areas slighter farther away from railroads suffer, as economic activity agglomerates around the railroads. However, this analysis is not feasible in our context, as the average distance between railroad stations (e.g., North and South directions) in colonial Malaya is only roughly 6 km. Studying an area beyond 6 km would then result in estimating the impact of another station. Nevertheless, the positive coefficients of our horizontal spillover analyses (e.g., East and West directions) suggest no area within 10 km suffers from agglomeration shadow.

[37]See Appendix A12 for 1967 map showing the location of agglomeration centers. We used 1967 because it lies almost in the middle of 1931 (the completion of third phase of railroad

agglomeration centers including a "dummy" for and "number" of agglomeration centers in a given cell at 10 km^2 (i.e., 0.09×0.09 decimal degree) level. This allows us to estimate the effect of historical rail stations on current economic activity through forming agglomeration centers using a two-stage least-squares instrumental variable (2SLS-IV) approach.

Our results are summarized in columns 1–2 of Table 5. Panel A contains the effect of agglomeration centers on night lights intensity (i.e., second stage), while Panel B shows the impact of railroad stations on agglomeration centers (i.e., first-stage). We first delve into the first-stage analysis. Interestingly, both coefficients in the bottom panel of columns 1 and 2 are positively significant, indicating that i) cells with railroad stations are 21% more likely to have at least one agglomeration center, and ii) every 100 cells with rail stations contain around 78 agglomeration centers on average. Nonetheless, these results do not provide any causal link, because these agglomeration centers might already exist prior to the construction of railroad stations. We resolve this issue by computing the change in agglomeration centers before and after railroad networks were completed. In particular, we geo-referenced the location of 1922 agglomeration centers.[38] We then calculate the difference in the numbers of agglomeration centers between 1922 and 1967, and estimate the effect of railroad stations on such changes. Column 3 in Panel B of Table 5 reports a positively significant coefficient, suggesting railroad stations trigger the formation of agglomeration centers in the surrounding areas.

Moving to the second-stage analysis, we find that agglomeration centers explains night lights intensity to the present. Panel B in Table 5 shows that cell with at least one agglomeration center had night lights intensity of 21.7 DN higher than those without agglomeration centers.

construction) and 1992 (the year of our night lights intensity data) period.

[38]This is the earliest data available to us on the location of agglomeration centers before railroad network was completed; the 1922 map showing location of agglomeration centers is given in Appendix A13.

Likewise, cells with an additional agglomeration center had higher night lights intensity of 5.75 DN. Our findings concurs with Krugman (1991b) theory, indicating that economic development is gained from improved railroad access mainly through the agglomeration economies with the clustering of people and businesses.

Marshall (1920) proffered a theory of agglomeration stating that firms and labor will conglomerate to reduce transport costs. As such, we aim to explore whether rail stations trigger agglomeration through population or firms. First, we rely on spatial distribution of population from *WorldPop* and mapped the 2000 population data into a 0.01×0.01 decimal degree to obtain the population count for each cell.[39] This newly constructed data set allows us estimating the effect of rail stations on the size of population at 1 km^2 level. Our estimate in column 1 of Table 6 reveals that cells with rail stations, on average, has agglomerated approximately 473 people more relative to its comparison cell. This finding supports the path-dependence hypothesis: economic advantages gained from rail stations translates into the agglomeration of population to the present. Our finding is in line with Atack et al. (2010); Hornung (2015); Berger and Enflo (2017).

Moving on, the extant literature suggests that railroads lead to reductions in trading costs or increases in market access and trade volume (Donaldson and Hornbeck, 2016; Donaldson, 2018). In a similar vein, Atack, Jeremy and Haines, Michael R and Margo, Robert A (2008); Duranton and Turner (2012); Banerjee et al. (2020) argued that lower trading costs and greater market accessibility stimulate greater economic growth through increases in the size of firms. We adopt this reasoning in our context and hypothesize that firms benefit by clustering around rail stations. We check this by using firm-level data from The 2015

[39]We use the population data for 2000, which is the earliest available population data. WorldPop developed spatially gridded population estimates through data collected from each country's population and housing census.The methodology of data construction can be found in WorldPop website, https://www.worldpop.org/project/categories?id=3.

Malaysia Enterprise Survey conducted by the World Bank. The data set consists of 1,000 enterprises in the manufacturing and service sectors, covering both Peninsular and East Malaysia.[40] We matched the location of these enterprises with our data on rail stations at the Mukim (i.e., sub-district) level.[41] For demonstration, Figure 4 displays the spatial distribution of firms partially. Although the establishment of firms are quite spread, but cities that enjoy largest growth in number of firms are those located closer to the railroad stations. This visual distribution of firms along with rail stations advocates for a positive nexus between them.

We formally estimated the effect of rail stations on the size of firms to the present. By doing so, we adopt the night lights intensity of 2013 because some firms were only established after 1995. Unfortunately, the data set did not provide the exact amount of current employee for each firm, but it categorized the current firm size into small (5–19 employees), medium (20–99 employees) and large (more than 100 employees). To improve the validity and accuracy of our results, we conduct the analysis using lower-bound, mid-point and upper-bound values of each category. Since no data are available on the upper-bound value of current firm size under category of large firms, we conduct a reasonable estimation based on the availability of data.[42] The results are provided in columns 2–4 of Table 6. All coefficients are positive and

[40]The sample was selected using a stratified random sampling method. Three levels of stratification were used, which are industry, establishment size and region. Hence, the sample represents an unbiased estimate of the population.

[41]We include 852 enterprises, located in 109 Mukims in Peninsular Malaysia, where 58 Mukims had station access and 51 Mukims did not; a map showing the spatial distribution of enterprises is provided in Appendix A14.

[42]For instance, the dataset provides the exact number of full-time employees employed when the firms began operation. We divide the reported number of employees in the start-up year from 748 firms into three categories: small, medium, and large firm (same range explained previously). We find that both initial and current firm sizes have a moderately high correlation of 0.6137, indicating the initial firm size reasonably reflects the current firm size. Therefore, we use the firm size of 650, the 99th percentile value, as our estimation for the upper-bound value of current firm size. The largest firm in the sample has starting employee

significant at a 5% level, indicating that firms located in Mukims with railroad stations had more employees. Our finding supports Atack, Jeremy and Haines, Michael R and Margo, Robert A (2008) in that railroads lead to an increase in the number of factories. Hornung (2015) also found that firms located near railroad access enjoy higher growth. [43] Overall, our analyses on the concentration of population and firms around rail stations suggest that historical rail network influences today's economic activity through fostering agglomeration centers.

5.4. Robustness, Placebo and Falsification Checks

In this section, we start with addressing the potential concern of endogeneity related to location bias. Rail stations might be built in areas that had relatively higher potential of economic growth or areas that had already been thriving prior to the construction of railroad network. Such pre-existing conditions could plague our identification and contaminate our estimates. We have already tackled this location bias in all of our estimation models by controlling for historical tin mining and rubber cultivation areas, as colonial rulers had chosen the location of rail stations strategically for expropriating natural resources. Now, we have further augmented our specification with an additional control that captures the spatial variation in rail stations from the straight line between its nearest major stations,

of 2,500 with several other firms having more than 1,000 employees. Hence, we used the value at the 99th percentile, excluding the huge outliers to avoid overestimation of the current firm size resulting in upward bias in our analysis.

[43] In attempt to understand the relative importance of channels discussed, we adopt similar approach conducted by Flückiger et al. (2021). By including agglomeration centers and population as a control in our benchmark analysis, we are able to observe the strength of each channel on the change in night lights intensity. Our result suggests that population change is the main channel in which railroad station affects economic activity. Firm analysis were not included as data is not available at the granular level to re-estimate the benchmark analysis. Details of this analysis is explained in Appendix A15.

as explained earlier in Section 4.2.[44] Column 1 of Table 7 shows that the coefficient is still positively significant and slightly larger in magnitude than our benchmark. This slightly higher coefficient possibly because of the downward biased in the benchmark estimates as the location choice of rail stations were intentionally deviated to connect regions with lower economic growth.[45]

Second, we attempt to resolve any potential "migration bias" as there is an influx of Chinese and Indian migrants during the British colonization period. As explained in Section 4.2, we incorporate extra variables accounting for historical Chinese and Indian population. The result is shown in column 2 of Table 7, where the coefficient is smaller than our benchmark analysis. This concords with our agglomeration argument, as controlling for newly conglomerated population made our estimate slightly smaller.

Our third robustness checks include additional controls of *terminal* and *junction* stations into the estimation model. We define terminal as the first and last stations of each rail line route while junction as stations intersecting two or more routes. The reasoning is that these stations are likely to be economically more "significant" stations, which are supposed to facilitate higher level of economic activity. Our result is presented in column 3 and 4 of Table 7. Unsurprisingly, both terminal and junction stations have had higher level of night lights intensity than others. This comforts our identification in that the variations in stations in terms of its economic significance are consistent with spatial differences in economic activity across stations.

Next, we conduct several placebo and falsification tests to verify whether our estimates

[44]Railroads are supposed to be built straight for cost minimization; any deviation in railroads from the straight line are likely due to localized factors that might trigger endogeneity in our estimation setting.

[45]Hornung (2015) also found that the estimates using straight lines are higher than it respective OLS results, suggesting that railroads might be assigned to disadvantaged regions.

capture the true effects of railroad stations. First, we artificially construct a placebo station dummy by randomly selecting cells and assigning those cells as if there are rail stations. Using this artificially constructed placebo station dummy, we re-estimate our benchmark model. The placebo dummy does not produce statistically significant results, as observed in column 5 of Table 7. This result suggests that our estimates in this study are likely to serve as the causal relationship, rather than an artefact of statistical correlation.

In the subsequent analysis, we attempt to understand whether historical stations that are not in service have any impact on economic activity to the present.[46] We do so by including an additional control for abandoned rail stations in our benchmark model. The result is shown in column 6 of Table 7, in which we find that the coefficient of our outcome variable increases quite significantly to 14.7 (relative to 9.15 in our benchmark analysis). The coefficient of dummy for abandoned stations turns out to be a negative value of 8.39 DN. It implies that areas with abandoned colonial rail stations experience approximately a half of the economic benefits as compared with stations that are still in service. This result validates our path-dependence hypothesis, in which colonial rail stations, even if abandoned later, stimulate economic development to the present. Similar results were suggested by Jedwab and Moradi (2016), and Okoye et al. (2019) in the context of Africa. We also found similar evidence from a temporary closure of some rail stations during the Japanese occupation of colonial Malaya. In early 1940s, Japanese troops bombed some parts of the railroad network, which destroyed 40 rail stations. Most of them were eventually rebuilt.[47] We extended our benchmark model by incorporating a dummy for destroyed rail stations in column 7 of Table 7. Our result suggests that the coefficient for historical rail stations has increased to 9.70 after controlling for the temporary closure of some stations during the Japanese occupation. We find a similar

[46] Appendix A16 provides a map showing operating and abandoned stations at present.

[47] Railroad network and stations that were destroyed during the Japanese invasion are shown in Appendix A17.

pattern when we have controlled for both abandoned and destroyed stations together, as shown in column 8.

Our falsification tests on the abandoned and destroyed stations manifest a the strong path dependence argument. Even if these stations were permanently removed or destroyed in wars, they still influence economic growth trajectory in the long-run. One reason could be that the colonial rulers run tin mining and rubber cultivation operations by hiring migrant workers mainly from China and India. They immigrated to Malaysia in groups, and used to live collectively. Such a communal structure made their adjustment cost higher to move away even if when natural resources have been exhausted by the colonizers. This is consistent with Krugman (1991a) "adjustment cost hypothesis" where historically important locations will thrive today if the adjustment cost of inhabitants is high. Besides, rubber cultivation was replaced by palm production in Malaysia, which restricted local labor force moving away and even attracted new immigrants moving in such agglomeration centers.

We also address the concern of omitted variable bias. Despite our attempt to control for several observables as well as state dummy, our estimates might still suffer from exclusion of unobservable factors that could be confounded with rail stations and economic activity. We adopted the approach of Oster (2019) to estimate our bias-adjusted treatment effects. We start by following the assumption of Nunn and Wantchekon (2011), where unobservables explain the outcome as much as observables do. Formally, we assume $R_{max} = \tilde{R} + (\tilde{R} - \dot{R})$, where $\tilde{R}$ stands for R-squared of the model with all controls, $\dot{R}$ represents R-squared of the model without controls while R_{max} is the R-squared of the hypothetical model in which all relevant observables and unobservables are controlled for. Using this assumption, we estimate the bias-adjusted treatment effects of rail stations on night lights intensity. The omitted variable bias-adjusted estimate is 7.70, as shown in column 1 of Table 8. This is slightly lower than our benchmark estimates of 9.15. We denote this condition such that selection of unobservables is equal to selection of observables as $\delta = 1$. Likewise, we report the bias-adjusted effect with conditions of $\delta = 0.5$ and $\delta = 0.1$ in columns 2–3 respectively, finding similar results. However, Oster (2019) indicated that the bias-adjusted treatment effect obtained from this condition might be misleading if R_{max} is relatively small. Therefore, the suggested R_{max} to be used is $R_{max} = 1.3\tilde{R}$, or 1.3 times the R-squared of the model with controls. We replicate the bias-adjusted treatment estimates, and the coefficient reduces slightly to 6.67. Similarly, there is also minor reduction in the bias-adjusted effects under the condition $\delta = 0.5$ and $\delta = 0.1$, respectively. Nonetheless, the signs of coefficients remain positive, suggesting that our benchmark analysis is robust to omitted variable bias, and unlikely to be driven by unobservable factors.

Next, we verify our benchmark table using an alternative data source as the outcome variable. Gibson (2021) finds that the night lights data from the VIIRS are more precise than the DMSP data as it has greater spatial resolution, no blurring and geo-location errors. Empirically, Gibson et al. (2021) compare the accuracy of both VIIRS and DMSP data in predicting the GDP of developing countries including Indonesia, China and South Africa. They find that VIIRS data are a better proxy for local economic activity in these developing countries as compared to DMSP data. However, the downside of VIIRS data is that the data is only available after 2012. Hence, we utilized a harmonised night lights between both VIIRS and DMSP data source generated by Li et al. (2020) as our alternative outcome variable. [48] We rerun Table 2 and obtained qualitatively similar results. The full table is summarised in Appendix A18.

Finally, We estimate the economic effects of rail stations on night lights intensity annually from 1992 to 2013. Our results are displayed in Figure 5. Interestingly, the general trend

[48]Studies including Martinez (2022) and Widmer and Zurlinden (2022) have also used this newly harmonised night lights data as measurement for economic development.

shows that night lights intensity in our treatment cells increases gradually over time, from 7.19 DN in 1992 to 15.2 DN in 2013. This suggests the economic impact from colonial rail stations is accumulated over time: the longer a region had access to rail stations, the larger economic gains it enjoys.

6. Conclusion

This paper proposed a novel framework for identifying the long-run economic impact of railroad network in colonial Malaya. We provide evidence that agglomeration gains geared by colonial rail stations persisted today to understand spatial differences in economic activity. Drawing upon this strand of literature, we uncovered new evidence on the extent to which rail stations affect economic activity to the present. We differ from extant studies by examining the economic impact of rail *stations* instead of naive rail *lines*. Our disaggregated approach of constructing a novel data set on historical rail stations enables us to contribute to the literature in two major ways. First, we address any potential endogeneity concern by comparing cells with and without rail stations located in close vicinity that were otherwise similar. Second and more importantly, the station-level data allows us to examine how railroad network propagates its agglomeration and spillover effects.

Our results show that regions with colonial rail stations have enjoyed larger economic benefits to the present, even if they are not in operation (e.g., abandoned or destroyed) today. We identify the emergence of agglomeration centers (e.g., clusters of population and firms) as an underlying mechanism through which economic activity is generated around rail stations. Exploring the agglomeration effect, our estimates indicate that the effects of colonial stations are highly concentrated around rail stations, while the spillover effect spreads as far as 10 km away.

We provide a comprehensive historical account to understand the economic impact of colonial railroads over time. Our paper, to the best of our knowledge, is the first attempt to analyze the persistent economic impact of historical rail stations in Malaysia. As such, we venture into the less-explored developing countries and South-East Asian region regarding transportation infrastructure. The policy implication of our study could be far-reaching and not limited to Malaysia. This study emphasizes the importance of railroad infrastructure in stimulating long-term economic growth in that the economic benefits of railroad network could continue to be accumulated over time. Our findings support path dependence of historical railroad stations on today's economic activity, suggesting that infrastructure development can have a long-term impact on the spatial dispersion of economic activity. This paper may provoke further studies especially whenever new data sets will be available. For instance, some stations could be used in terms of moving passengers or freighting goods; delineating such effects are likely to provide new insights. Besides, some stations might be used for local resource extractions, and distinguishing the effect of such stations from others may improve our understanding on the persistence of historical institutions. That is, historical accounts of railroad network at station level could open up a new avenue for research.

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Widmer, Philine and NoÃ©mie Zurlinden, "Ministers Engage in Favoritism Too," *Journal of Public Economics*, 2022, *213*, 104707.

World Bank, "Annual Report 2019 Lending Data," 2019.

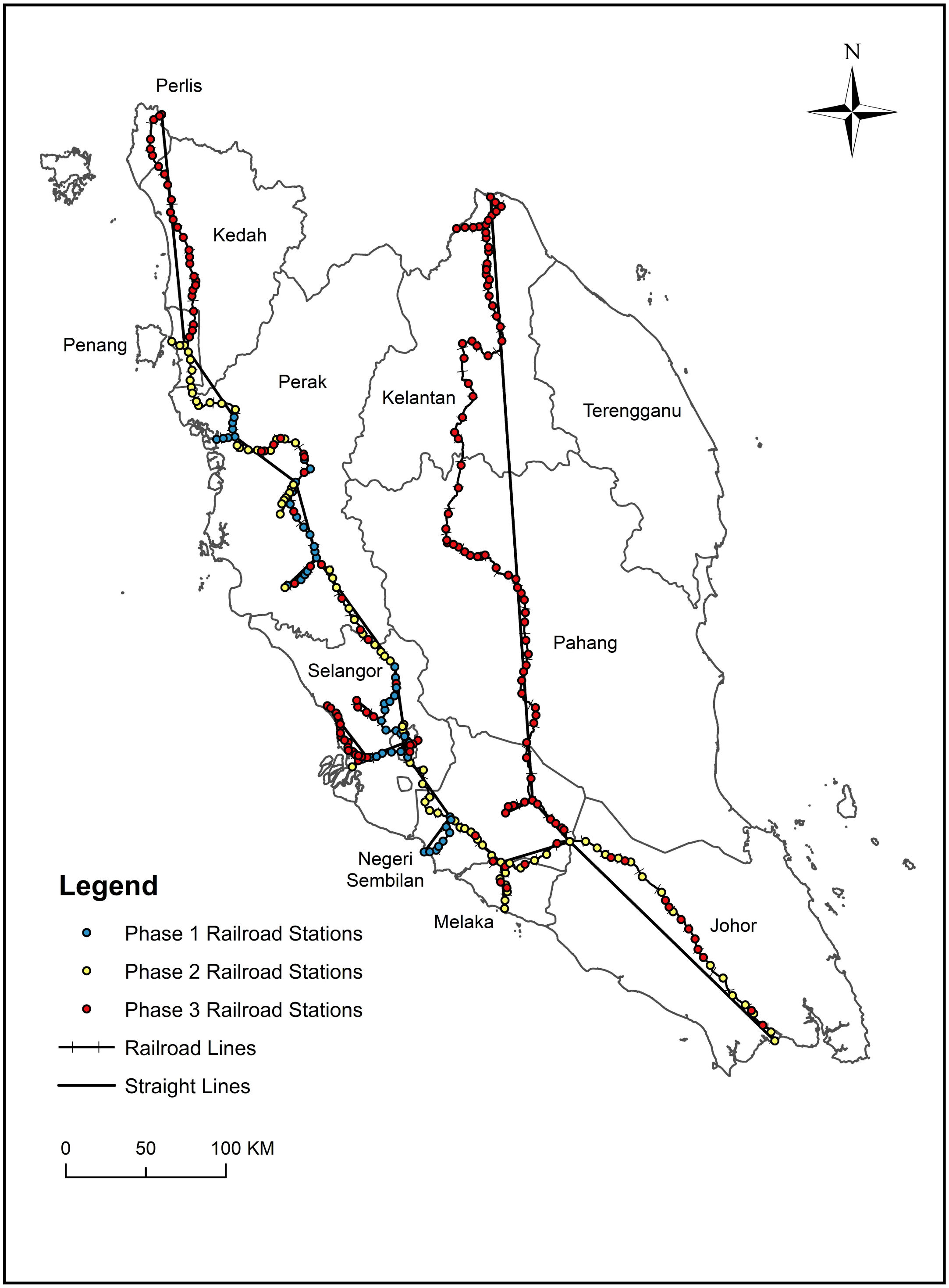


Figure 1: Historical Railroad Network in Peninsular Malaysia

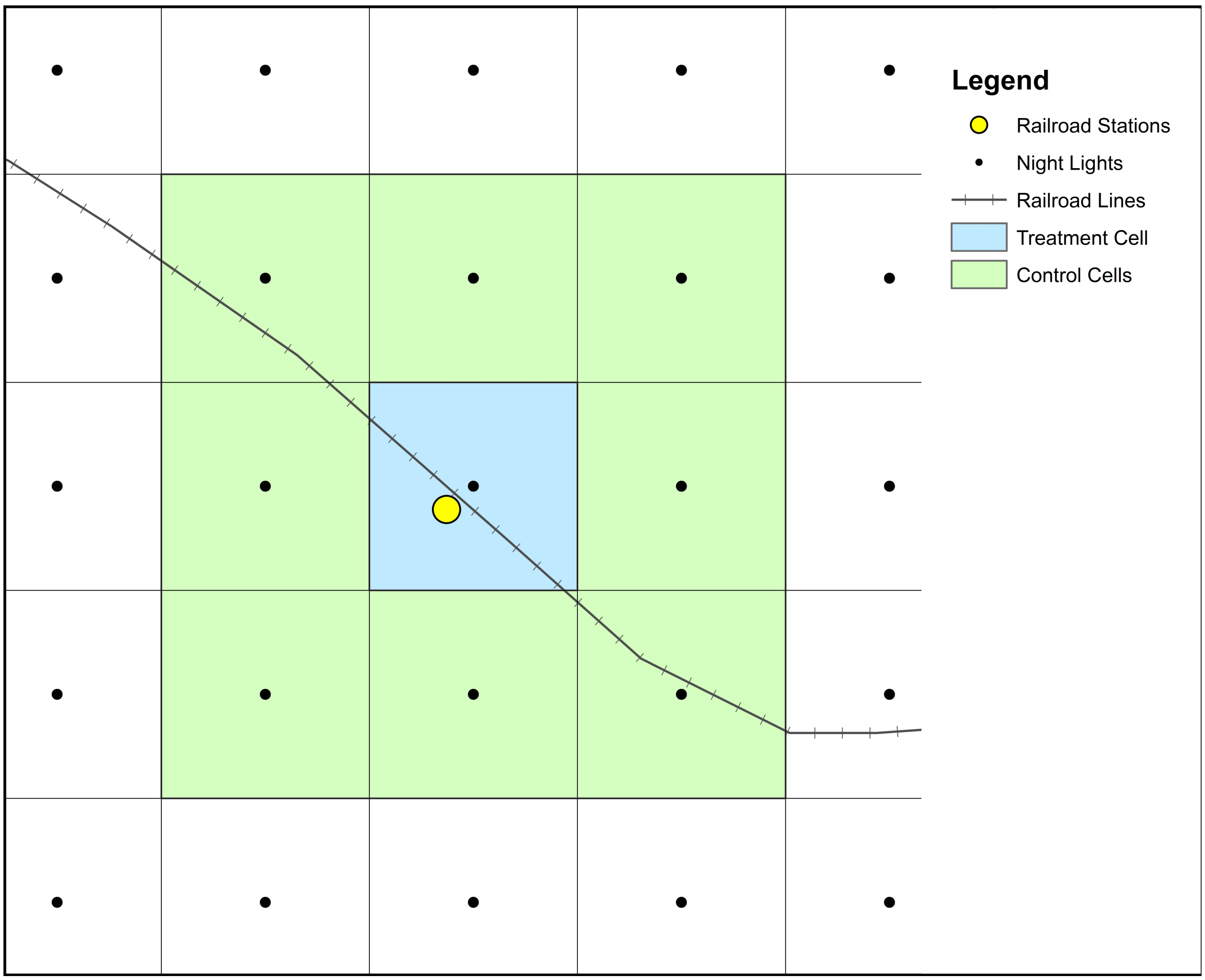


Figure 2: Treatment and Control Cells

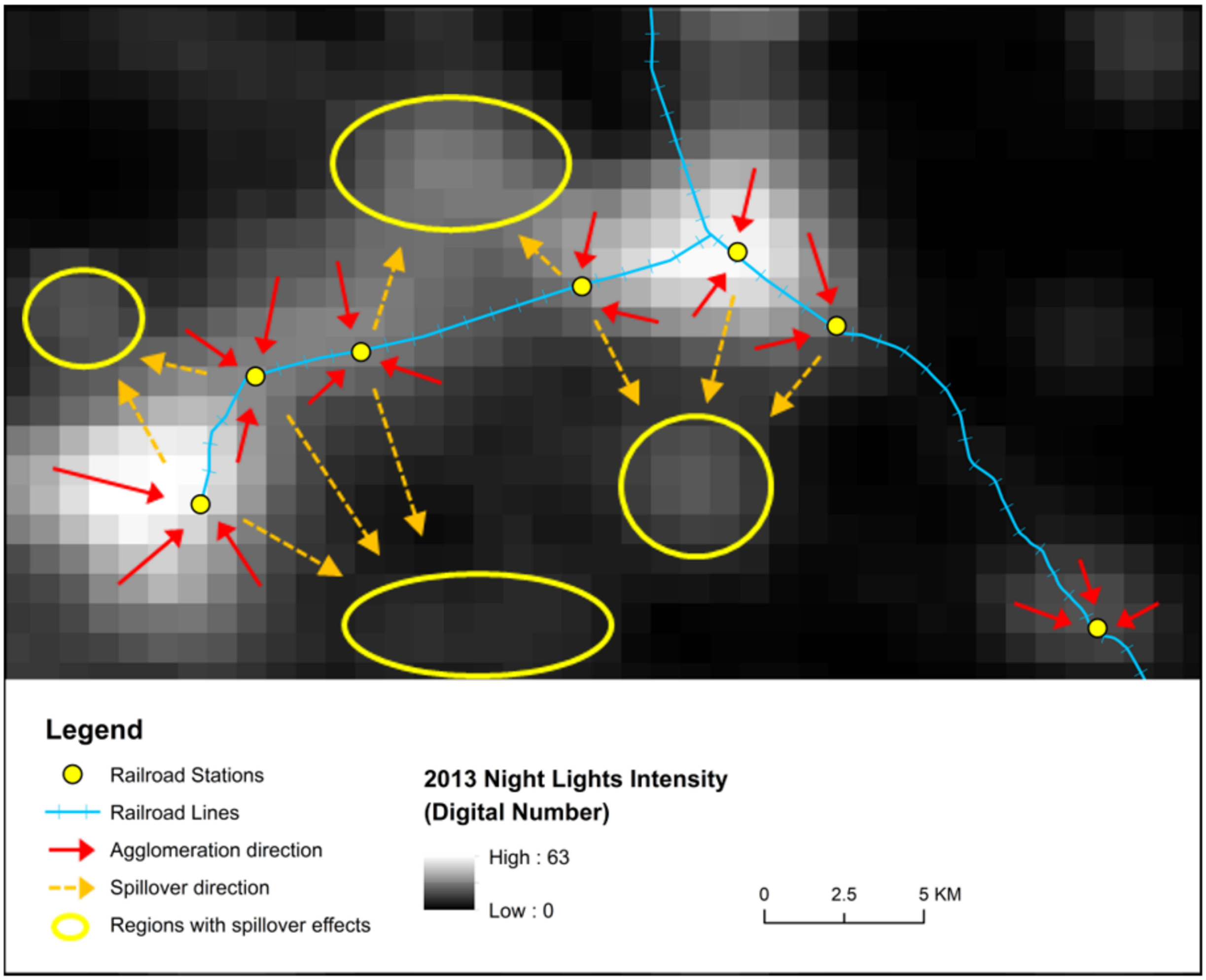


Figure 3: Agglomeration and Spillover Effects

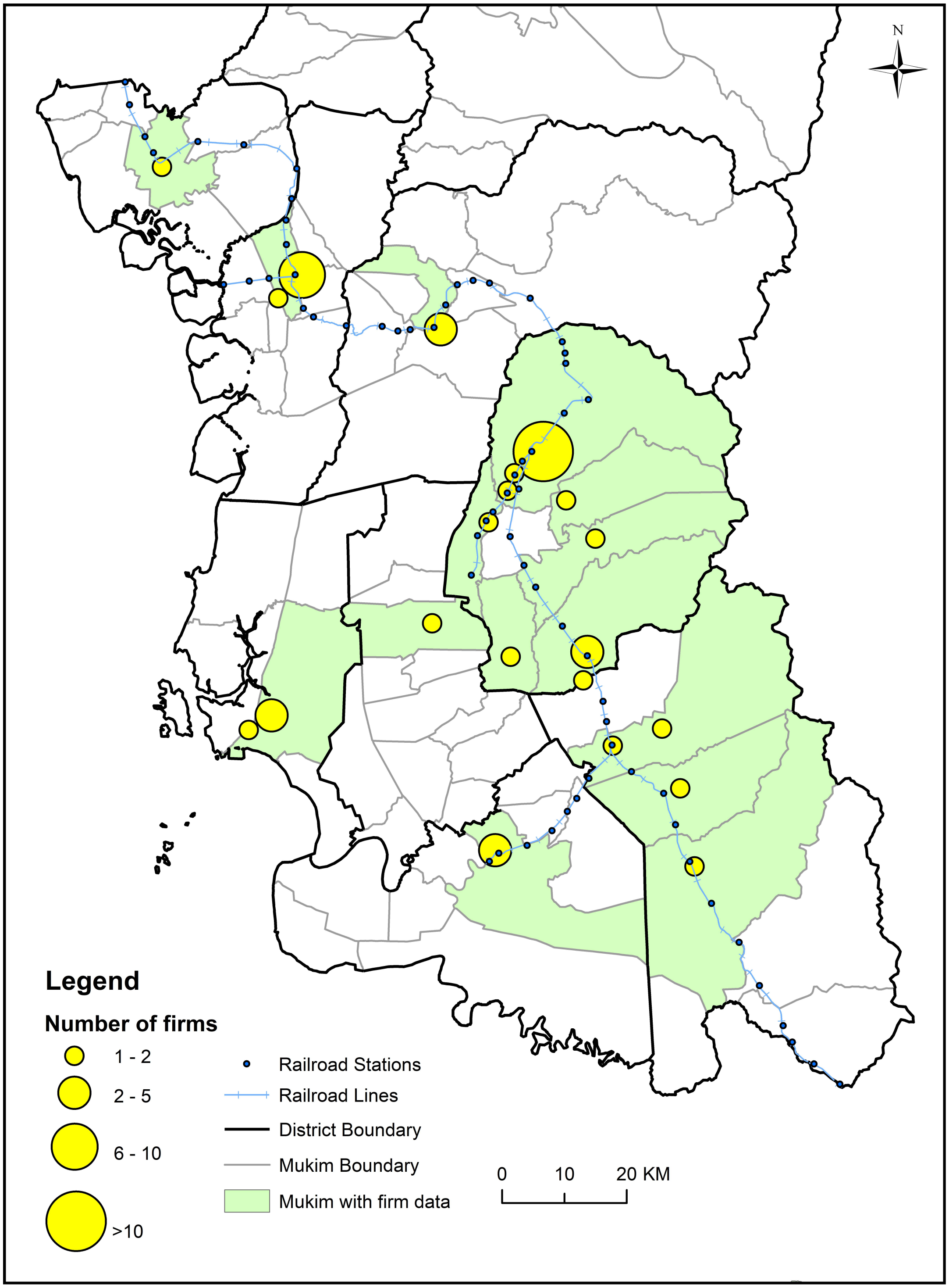


Figure 4: Spatial Distribution of Firms and Railroad Stations at Southern Perak in 2015

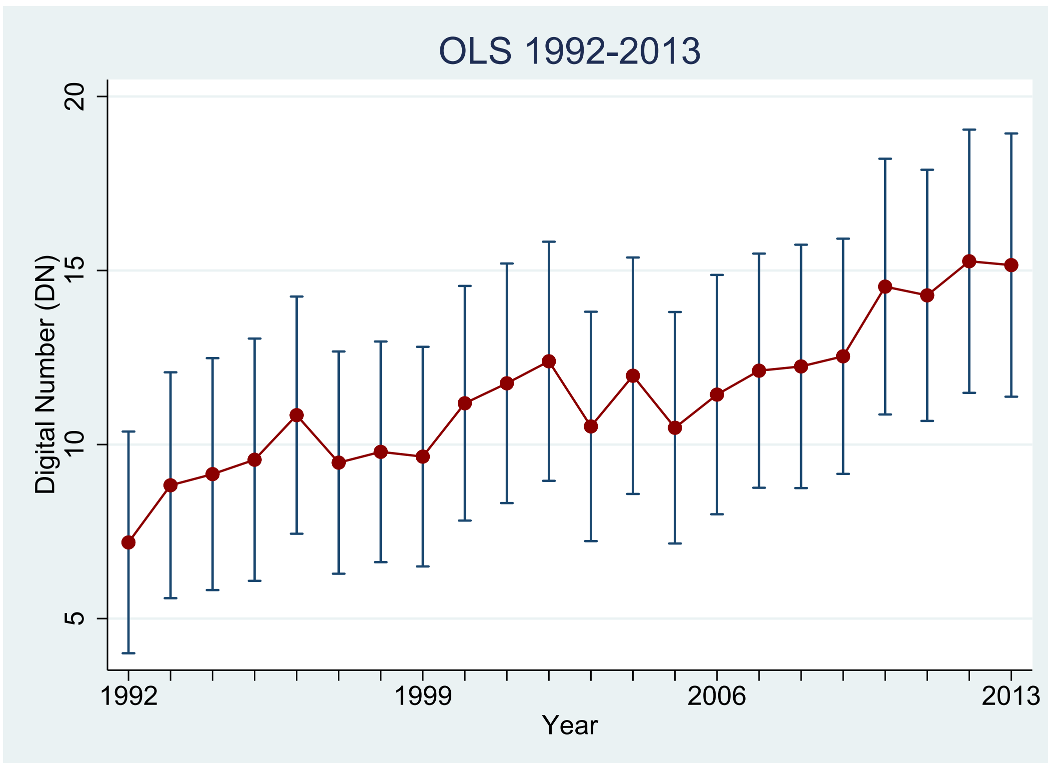


Figure 5: Economic Impact of Colonial Railroad Stations from 1992 to 2013

Table 1: Summary statistics (mean) for treated and control cells

	Station	Non station
	(1)	(2)
Average Nightlights Digital Number 1992-1994	17.736	2.499
Major river dummy	0.397	0.173
Coastline dummy	0.019	0.016
Terrain Ruggedness Index (in meters)	25.145	101.447
Tin mining area dummy	0.27	0.074
Rubber cultivation area (in square kilometres)	0.522	0.181
Number of cells	307	106,765

Note: This table presents the mean of each variable for cells with railroad stations (column 1) and cells without railroad stations (column 2).

Table 2: Persistent impact of colonial railroad stations

	Dependent Variable: Average Digital Number (DN), 1992–1994						
	Peninsular Malaysia	Phase 1	Phase 2	Phase 3	West coast	East coast	Truncated Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Station access by 1931	9.15***	13.8***	13.8***	5.16***	11.2***	1.95**	1.22***
	(1.672)	(4.271)	(2.371)	(1.660)	(1.835)	(0.889)	(0.370)
Major river	0.28**	0.27**	0.26*	0.28*	0.59**	-0.026	1.31
	(0.139)	(0.136)	(0.134)	(0.137)	(0.231)	(0.107)	(0.978)
Coastline	4.54***	4.45***	4.50***	4.43***	3.99**	6.41**	16.8
	(1.349)	(1.327)	(1.341)	(1.325)	(1.532)	(2.901)	(10.978)
ln(Terrain Ruggedness Index)	-0.12	-0.12	-0.12	-0.12	-0.054	-0.20	-1.42*
	(0.138)	(0.138)	(0.138)	(0.138)	(0.202)	(0.187)	(0.787)
Tin mining area	2.60*	2.57*	2.57*	2.57*	2.54	0	5.54
	(1.523)	(1.511)	(1.513)	(1.507)	(1.540)	(.)	(3.582)
Rubber cultivation area	4.10***	4.13***	4.11***	4.13***	4.18***	3.83**	-0.19
	(1.053)	(1.054)	(1.053)	(1.057)	(1.210)	(1.345)	(2.202)
State Dummy	yes	yes	yes	yes	yes	yes	yes
Observations	107072	106821	106851	106930	55091	51981	2546
R2	0.26	0.25	0.25	0.25	0.27	0.049	0.37

Note: Using the "Cell Approach" at 1 km^2 level, this table shows OLS estimates regressing average night lights intensity (in DN) for 1992-1994 on the access to historical rail stations. In parentheses are the robust standard error clustered at the district level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 3: Agglomeration effect

Dependent Variables	Average Digital Number (DN), 1992–1994						Average Night Lights Concentration Index (DN), 1992–1994					
	Cell Approach				Ring Approach		Cell Approach				Ring Approach	
	Full Sample		Truncated Sample		Full Sample		Full Sample		Truncated Sample		Full Sample	
	9 km^2	25 km^2	9 km^2	25 km^2	9 km^2	25 km^2	9 km^2	25 km^2	9 km^2	25 km^2	9 km^2	25 km^2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Station access by 1931	8.35***	6.31***	4.37***	4.25***	8.07***	7.37***	0.47***	0.16***	0.49***	0.18***	0.48***	0.29***
	(1.628)	(1.364)	(0.802)	(0.854)	(1.591)	(1.548)	(0.068)	(0.035)	(0.068)	(0.038)	(0.065)	(0.049)
Observations	107072	107072	13015	22919	107072	107072	107072	107072	13015	22929	107072	107072
R^2	0.27	0.28	0.35	0.31	0.27	0.29	0.010	0.0044	0.022	0.0080	0.011	0.0085

Note: This table shows OLS estimates regressing average DN for 1992-1994 on historical railroad station access at 9 km^2 and 25 km^2 level using both cell size approach and ring approach Controls include river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. The radius for ring approach is 1.88 km for 9 km^2 level and 3.13 km for 25 km^2 level respectively. The radius for extended ring analysis is double of the radius for ring approach. In parentheses are the robust standard error clustered at the district level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 4: Spillover effect

	Dependent Variable: Average Digital Number (DN), 1992–1994					
	3 km	5 km	10 km	15 km	20 km	25 km
	(1)	(2)	(3)	(4)	(5)	(6)
Station access by 1931	5.88***	4.54***	3.29**	1.52	1.06	-0.16
	(1.465)	(1.474)	(1.403)	(1.217)	(1.100)	(0.582)
Observations	107072	107072	107072	107072	107072	107072
R^2	0.26	0.26	0.25	0.25	0.25	0.25

Note: This table shows OLS estimates regressing average DN for 1992-1994 on historical railroad station access at neighbouring cells of 3 km up to 25 km. Controls include river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. In parentheses are the robust standard error clustered at the district level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 5: Agglomeration economies as a potential mechanism

	Dependent Variable: Average Digital Number (DN), 1992–1994		
	(1)	(2)	(3)
	Panel A: Two-Stage Least Squares		
Dummy for agglomeration center, 1967	21.7**		
	(8.592)		
Number of agglomeration center, 1967		5.75***	
		(2.083)	
Change in agglomeration center, 1922–1967			7.04***
			(2.532)
	Panel B: First Stage for agglomeration centers in 1967		
Station access by 1931	0.21***	0.78***	0.63***
	(0.046)	(0.172)	(0.158)
F-statistics	64.41	82.66	98.65
Observations	107072	107072	107072
R^2	0.21	0.19	0.17

Note: This table shows the estimations of two stage least square instrumental (2SLS-IV) approach. The top panel reports the second-stage estimates while the bottom panel reports the first-stage estimates. First-stage analyses regress dummy for agglomeration centre in 1967, number of agglomeration centre in 1967 and change in number of agglomeration centre, 1922–1967 on historical railroad station access. Second-state analyses regress average DN at 1992–1994 on dependent variable used in first-stage estimates. Controls include river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. In parentheses are the robust standard error clustered at the district level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 6: Persistent impact of colonial railroad stations on population and firm

Dependent Variables:	Population, 2000	Firm Size, 2015		
	(1)	(2)	(3)	(4)
Station access by 1931	472.8***	6.76**	26.1**	45.5**
	(71.161)	[3.331]	[12.866]	[22.419]
Observations	107,072	852	852	852
R^2	0.34	0.10	0.098	0.098

Note: This table shows OLS estimates regressing population in year 2000 and firm size in year 2015 on historical railroad station access Controls include river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. In parentheses are the robust standard error clustered at the district level. In square brackets are the robust standard error. Robust standard error is used as firms data are only available at the mukims level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 7: Robustness, placebo and falsification tests

	Dependent Variable: Average Digital Number (DN), 1992–1994							
	Robustness checks				Placebo test	Falsification tests		
	Location bias	Migration bias	Terminal stations	Junction stations	Placebo stations	Abandoned stations	Destroyed stations	Abandoned & destroyed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Station access by 1931	11.5***	9.06***	8.25***	8.56***		14.7***	9.70***	15.0***
	(2.181)	(1.601)	(1.657)	(1.610)		(2.979)	(1.735)	(2.835)
Placebo stations					0.011			
					(0.338)			
Nearest spatial distance to straight line	-0.42***							
	(0.137)							
Chinese population in 1947		0.0000037						
		(0.000)						
Indian population in 1947		0.000015						
		(0.000)						
Terminal stations			17.2***					
			(5.507)					
Junction stations				13.2**				
				(6.168)				
Abandoned stations						-8.39***		-8.24***
						(2.592)		(2.590)
Stations destroyed during Japanese occupation							-3.27	-2.41
							(3.752)	(4.179)
Observations	107072	107072	107072	107072	107072	107072	107072	107072
R^2	0.26	0.26	0.26	0.26	0.25	0.26	0.26	0.26

Note: This table shows OLS estimates regressing dependent variables of average DN at 1992-1994 and DN at 2013 on historical railroad station access and placebo stations at 1 km^2 cell. Controls include nearest spatial distance to straight line, Chinese population in 1947, Indian population in 1947, terminal stations, junction stations, river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. In parentheses are the robust standard error clustered at the district level. sym*Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 8: Using selection on observables to assess bias from unobservables

	Selection in unobservable is equal to selection on observable ($\delta = 1$)	Selection in unobservable is smaller than selection on observable ($\delta = 0.5$)	Selection in unobservable is much smaller than selection on observable ($\delta = 0.1$)
	(1)	(2)	(3)
Table 3 Column 1: Controlled $\beta = 9.15$			
Bias-adjusted β for $R_{max} = \tilde{R} + (\tilde{R} - \dot{R})$	7.70	8.43	9.01
Bias-adjusted β for $R_{max} = 1.3\tilde{R}$	6.67	7.91	8.90

Note: This table shows the omitted variable bias-adjusted estimates for our benchmark results reported in Column 1 in Table 2. We employ Oster (2019) approach in accounting for the biases from unobservable.

Appendix

Appendix A1: List of Data Sources

Railroad Stations and Lines

- Map of the Malay Peninsula 1891 by Royal Asiatic Society of Great Britain and Ireland.
  https://nla.gov.au/tarkine/nla.obj-231529263
- Map of the Malay Peninsula 1898 by Royal Asiatic Society of Great Britain and Ireland.
  https://nla.gov.au/tarkine/nla.obj-231529372
- Map of the Malay Peninsula 1911 by Royal Asiatic Society of Great Britain and Ireland.
  https://nla.gov.au/tarkine/nla.obj-230048780
- Map of British Malaya 1921 by Federated Malay States Survey Department.
  https://nla.gov.au/tarkine/nla.obj-862725139
- Map of British Malaya 1922 by Federated Malay States Survey Department.
  https://nla.gov.au/tarkine/nla.obj-234685457
- Map of the Federated Malay States Railway 1932 by Federated Malay States Survey Department.
  https://projekkeretapikita.files.wordpress.com/2018/01/railway-map-1932-comp.jpg
- Malaya 1935 by Federated Malay States Survey Department.
  http://digital.sl.nsw.gov.au/delivery/DeliveryManagerServlet?embedded=true&toolbar=false&dps_pid=IE9186328&_ga=2.42891621.1150573020.1614315496-2118774323.1587701297
- Railways of Malaya 1943 by Great Britain War Office.
  https://nla.gov.au/tarkine/nla.obj-258232633
- Malaysia Railroad Lines in 2013 by International Steering Committee for Global Mapping and Department of Survey and Mapping Malaysia.
  https://earthworks.stanford.edu/catalog/stanford-tq319bk3902

Malaysia Boundary

- GADM.
  https://gadm.org/data.html

- Subnational units, Malaysia (WorldPop & Center for International Earth Science Information Network (CIESIN), Columbia University, 2018).
  https://www.worldpop.org/geodata/summary?id=24640

Night Lights

- Version 4 DMSP-OLS Nighttime Lights Time Series.
  https://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

Major River

- Major river – WMO Basins and Sub Basins, 3rd ed (GRDC, 2020).
  https://www.bafg.de/GRDC/EN/02_srvcs/22_gslrs/223_WMO/wmo_regions_node.html;jsessionid=961E7DC5AA48BD2467CD503869A8E1DF.live21302

Terrain Ruggedness Index (TRI)

- Terrain Ruggedness Index – Data and replication files for 'Ruggedness: The blessing of bad geography in Africa' (Nunn & Puga, 2012).
  https://diegopuga.org/data/rugged/

Tin Mining Area

- Map of the Malay Peninsula 1891 by Royal Asiatic Society of Great Britain and Ireland.
  https://nla.gov.au/tarkine/nla.obj-231529263

Rubber Cultivation Area

- Planting empire, cultivating subjects: British Malaya, 1786–1941 (Lee, 2017).

Historical Population Data

- A Report on the 1947 Census of Population, Malaya

Agglomeration Centers

- Map of British Malaya 1922 by Federated Malay States Survey Department.
  https://nla.gov.au/tarkine/nla.obj-234685457
- Malaya 1967 by Department of Survey and Mapping Malaysia.
  https://openresearch-repository.anu.edu.au/handle/1885/140524
  https://openresearch-repository.anu.edu.au/handle/1885/148333

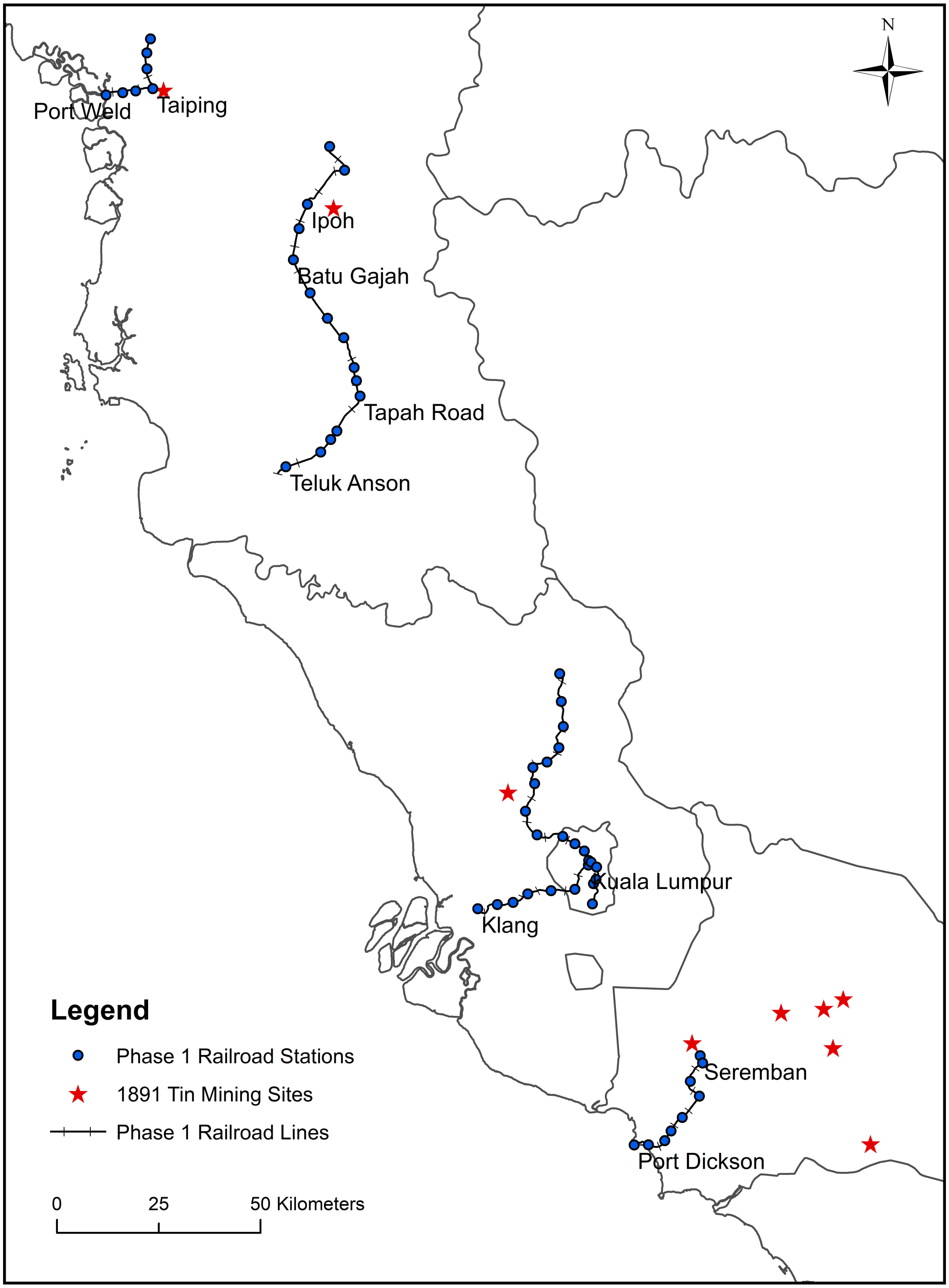
Population in 2000

- The spatial distribution of population in 2000 with country total adjusted to match the corresponding UNPD estimate, Malaysia (WorldPop & Center for International Earth Science Information Network (CIESIN), Columbia University, 2018).
  https://www.worldpop.org/geodata/summary?id=37379

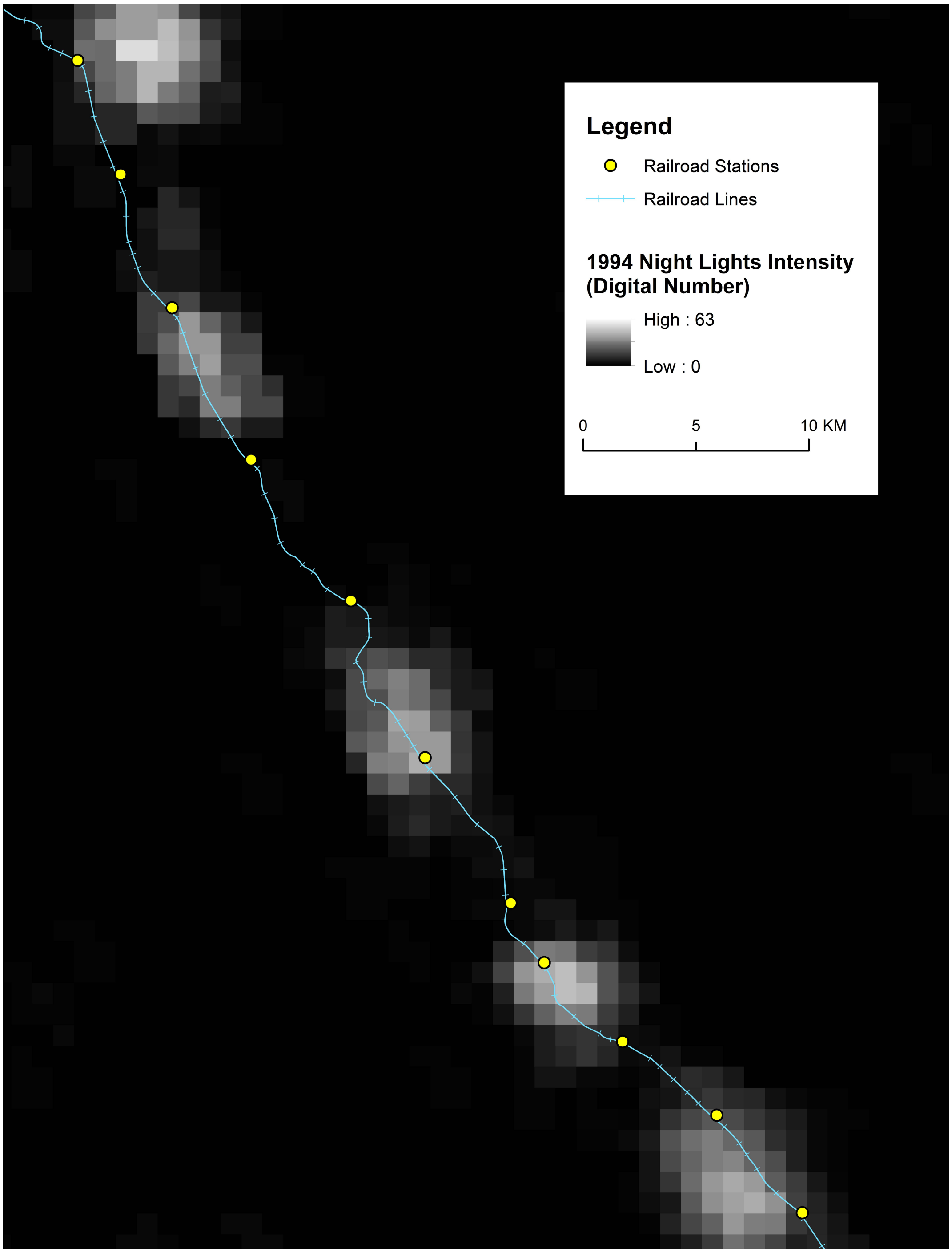
Firms data

- Malaysia 2015 Enterprise Survey data (World Bank, 2019).
  https://login.enterprisesurveys.org/content/sites/financeandprivatesector/en/library/library-detail.html/content/dam/wbgassetshare/enterprisesurveys/economy/malaysia/Malaysia-2015-full-data.dta

Appendix A2: Phase 1 Railroad Network



Appendix A3: Nightlights intensity around railroad network in year 1994



Appendix A4: Comparison of average nightlights intensity for control and treated cells by states

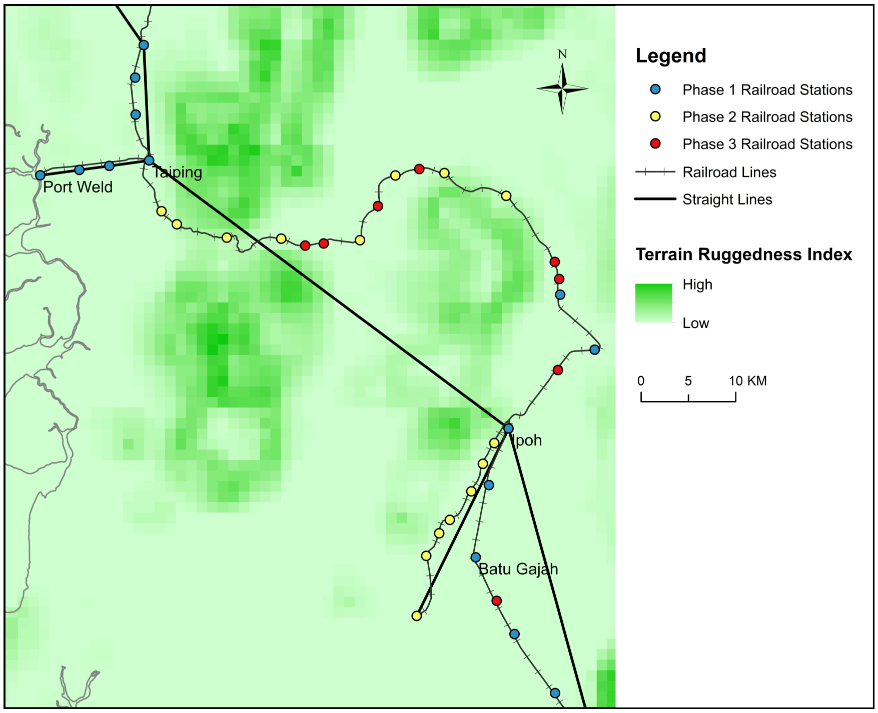
States	Average Nightlights Digital Number 1992-1994	
	Station	Non station
Penang	32.747	22.491
Melaka	14.954	8.271
Perak	14.071	1.864
Selangor	36.91	11.201
Negeri Sembilan	12.727	2.393
Pahang	2.964	0.877
Kedah	17.321	2.431
Perlis	13.755	4.222
Kelantan	5.687	0.892
Terengganu	-	1.469
Johor	17.669	2.976

Note: There are no railroad stations in Terengganu.

Appendix A5: Creation of Straight Lines

Several factors were taken into account in determining the starting and ending station of railroad lines. First, many initial railroad lines explicitly stating the aim of connecting two main areas. For instance, Port Weld to Taiping or Klang to Kuala Lumpur are explicitly stated. These stations will then be the starting and ending point of our straight lines. The second factor is the timing of railroad stations being built. Since phase two of railroad constructions are aiming to connect the lines built in phase one, the starting and ending stations of straight lines for phase two railroad line are then mostly the starting and ending stations of straight lines during phase one. Lastly, topography ruggedness is also taken into account in constructing the straight lines. From the map of railroad stations and topography ruggedness, we can see that some lines clearly are avoiding cutting through rugged areas at all cost. As such, we determine such areas as lines deviating from the straight lines. The explanation can be visualized in Figure A5.

Figure A5: Creation of Straight Lines



Appendix A6: Sample without Melaka

	Dependent Variable: Average Digital Number (DN), 1992–1994
	(1)
Station access by 1931	9.16***
	(1.727)
Observations	105734
R^2	0.26

Note: This table shows OLS estimates regressing average DN for 1992-1994 on historical railroad station access at 1 km^2 cell. Controls include river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. In parentheses are the robust standard error clustered at the district level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Appendix A7: Comparison between Rail Stations and Rail Lines

We first remove all cells with rail lines in our sample and replicate our benchmark analysis with this smaller sample. Removing all cells with rail lines ensures that we only capture the effect of railroad stations, not the rail lines. Generally, there is an increase in coefficients for all columns, except for the sample on the east coast that had negligible reduction, suggesting that railroad stations have a higher economic impact than rail lines. The results can be observed in Table A7a.

We then estimate the impact of rail lines by removing all cells with station from the sample, ensuring that we analyze solely the association between rail lines and economic development without any disturbance from railroad stations. Our result is shown in Table A7b, in which most columns report a lower coefficient than in Table 3, except for the sample on the first phase that had a minimal increase. Taken together, we argue that the higher coefficient of railroad stations suggests that stations, not rail lines, stimulate economic activity.

This result is expected because we can only access the railroad network from a station. One potential explanation for the significant positive coefficient from our rail lines analysis could be the spillover effect of railroad stations, which is discussed in depth in Section VIA. In brief, most rail lines are located near a station; hence, some economic impact can be felt in these cells as well. We also conduct an analysis with both rail lines and stations together as seen in Table A7c. Most of the coefficients are also lower than our benchmark analysis in Table 3, validating our claim that railroad stations are indeed the cause of economic development instead of railroad lines.

Additionally, analyzing rail lines allows us to reduce concerns that the positive impact of railroad stations from the earlier analysis are induced by factors other than the stations. For instance, many historical post offices in Malaysia are located near colonial railroad stations in Kuala Lumpur, Kuala Lipis, Malim Nawar, Batu Arang, and Gemas. Hence, there is possibility that we are indeed analyzing the impact of post offices instead of railroad stations. By using railroad lines as our independent variable, we analyze an area without post offices, but that rail line is near to a station. Thus, our analysis on rail lines is able to capture the real effect of railroad stations, further validating that railroad stations enhance economic development.

Table A7a: Persistent impact of historical railroad stations (sample without rail lines)

	Dependent Variable: Average Digital Number (DN), 1992–1994					
	Peninsular Malaysia	Phase 1	Phase 2	Phase 3	West Coast	East Coast
	(1)	(2)	(3)	(4)	(5)	(6)
Station access by 1931	9.47***	14.3***	14.1***	5.41***	11.6***	1.91*
	(1.734)	(4.293)	(2.406)	(1.715)	(1.897)	(0.924)
Observations	105419	105168	105198	105277	53881	51538
R^2	0.25	0.24	0.24	0.24	0.27	0.048

Note: This table shows OLS estimates regressing the average DN for 1992-1994 on historical railroad station access at 1 km^2 cell. Controls include river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. In parentheses are the robust standard error clustered at the district level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table A7b: Persistent impact of colonial railroad lines (sample without railroad stations)

	Dependent Variable: Average Digital Number (DN), 1992–1994					
	Peninsular Malaysia	Phase 1	Phase 2	Phase 3	West Coast	East Coast
	(1)	(2)	(3)	(4)	(5)	(6)
Railroad line access	6.87***	13.9***	8.80***	2.53	9.37***	0.14
	(1.493)	(3.508)	(1.814)	(1.606)	(1.565)	(0.785)
Observations	106765	105334	105731	105848	54851	51914
R^2	0.26	0.26	0.25	0.24	0.28	0.048

Note: This table shows OLS estimates regressing average DN for 1992-1994 on historical railroad line access at 1 km^2 cell. Controls include river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. In parentheses are the robust standard error clustered at the district level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

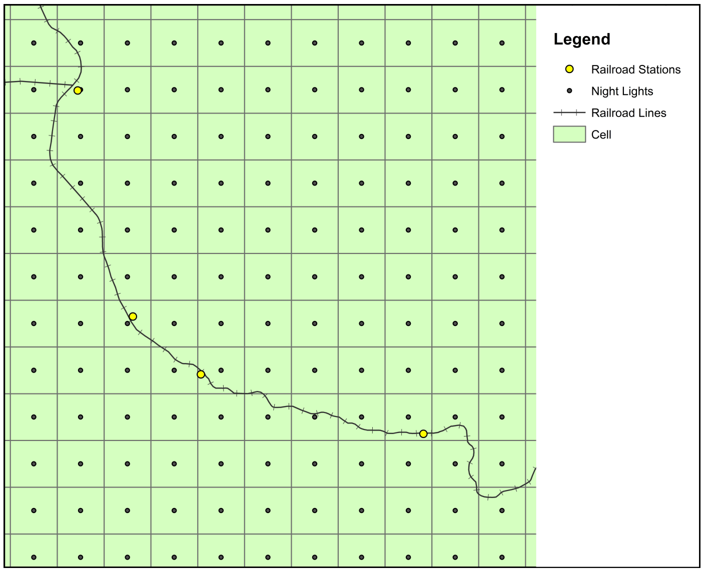
Table A7c: Persistent impact of historical railroad network (sample with both railroad stations and rail lines)

	Dependent Variable: Average Digital Number (DN), 1992–1994					
	Peninsular Malaysia	Phase 1	Phase 2	Phase 3	West Coast	East Coast
	(1)	(2)	(3)	(4)	(5)	(6)
Station and railroad line access	7.12***	14.2***	9.24***	2.80*	9.64***	0.32
	(1.516)	(3.607)	(1.823)	(1.607)	(1.591)	(0.784)
Observations	107072	105400	105845	105977	55091	51981
R^2	0.27	0.26	0.25	0.24	0.29	0.048

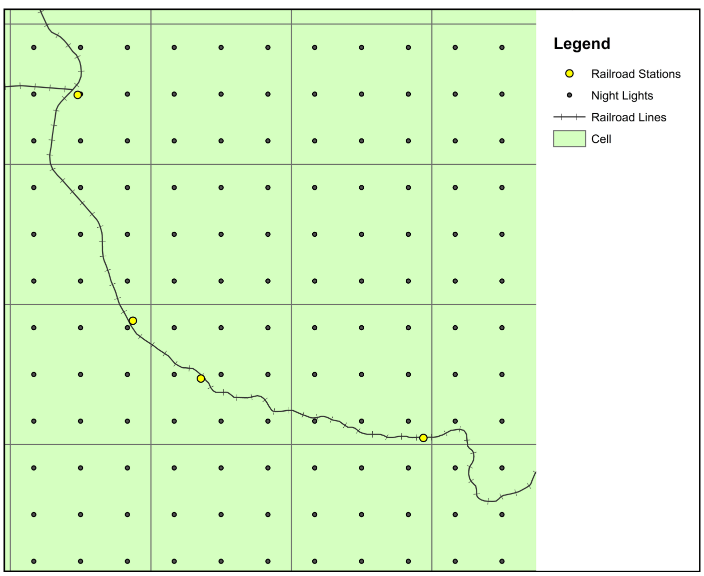
Note: This table shows OLS estimates regressing average DN for 1992-1994 on historical railroad station and line access at 1 km^2 cell. Controls include river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. In parentheses are the robust standard error clustered at the district level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Appendix A8: Spatial diagram of 1 km^2, 9 km^2 and 25 km^2 cell

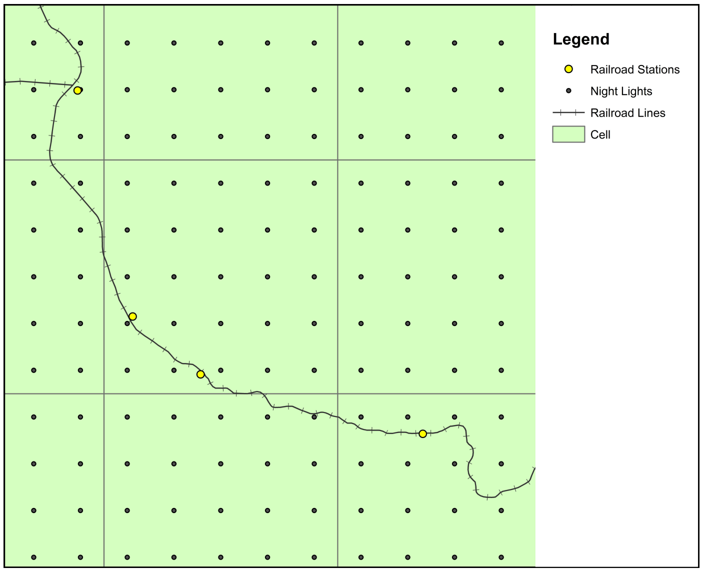
1 km^2 cell



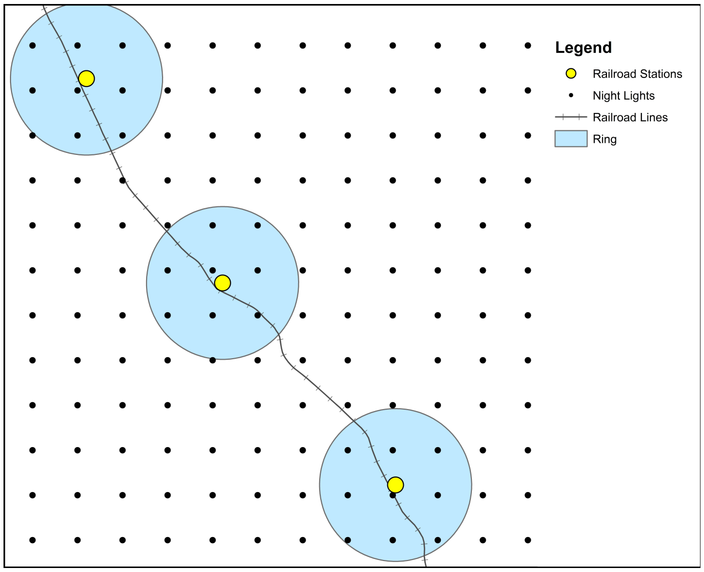
9 km^2 cell



25 km^2 cell



Appendix A9: Ring approach at 9 km^2 level



Appendix A10: Night Lights Concentration Index Analyses

Figure A10: Schematic of the Night Lights Concentration Calculation

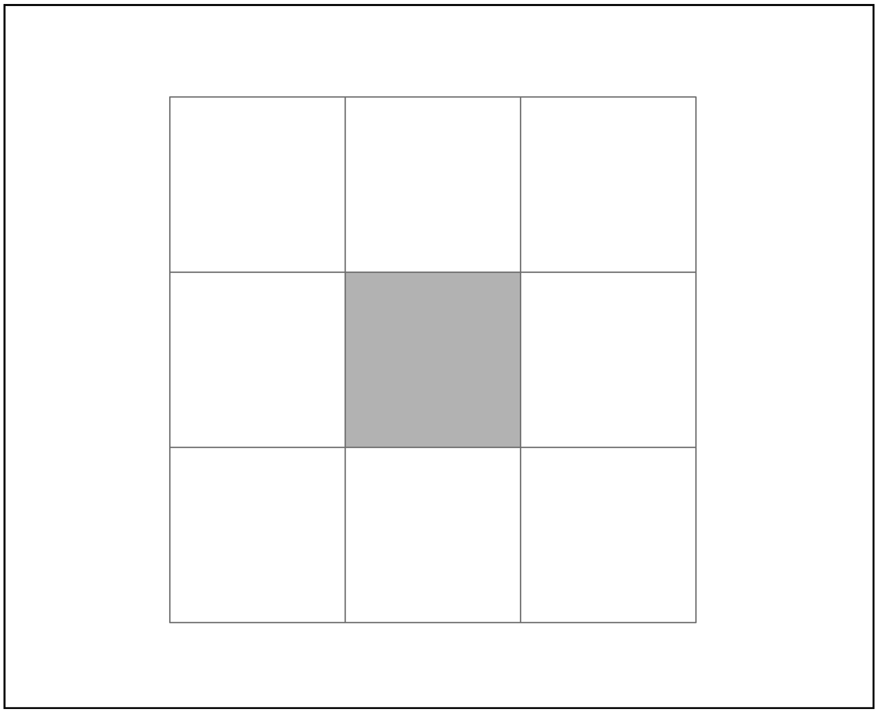


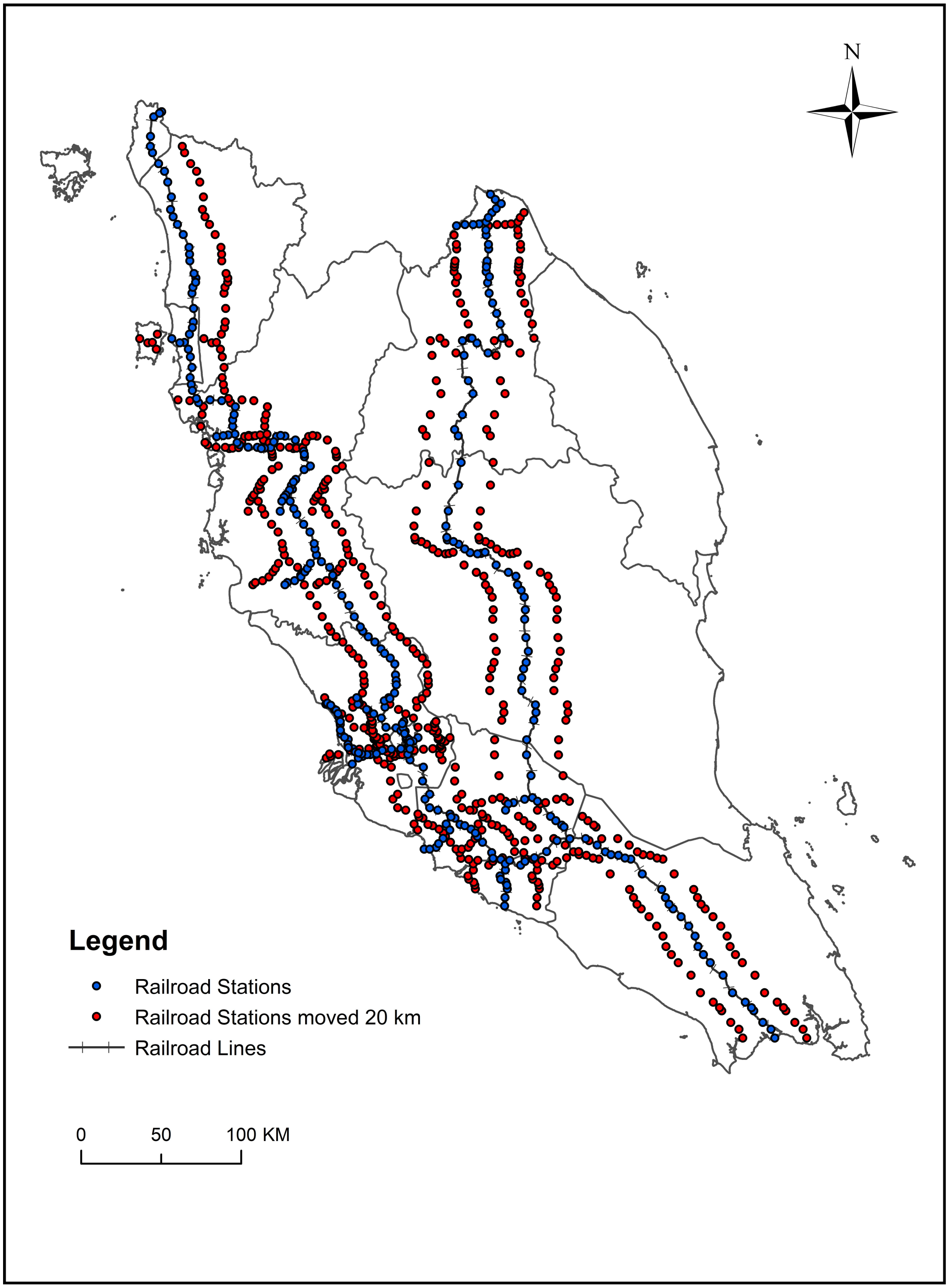
Figure A12 presents the visual diagram in calculating the night lights concentration index. The night lights concentration index of the center grey cell is given by the average difference of night lights intensity of the central grey cell and the eight adjacent white cells.

Appendix A11: Neighbouring Cells of Railroad Stations

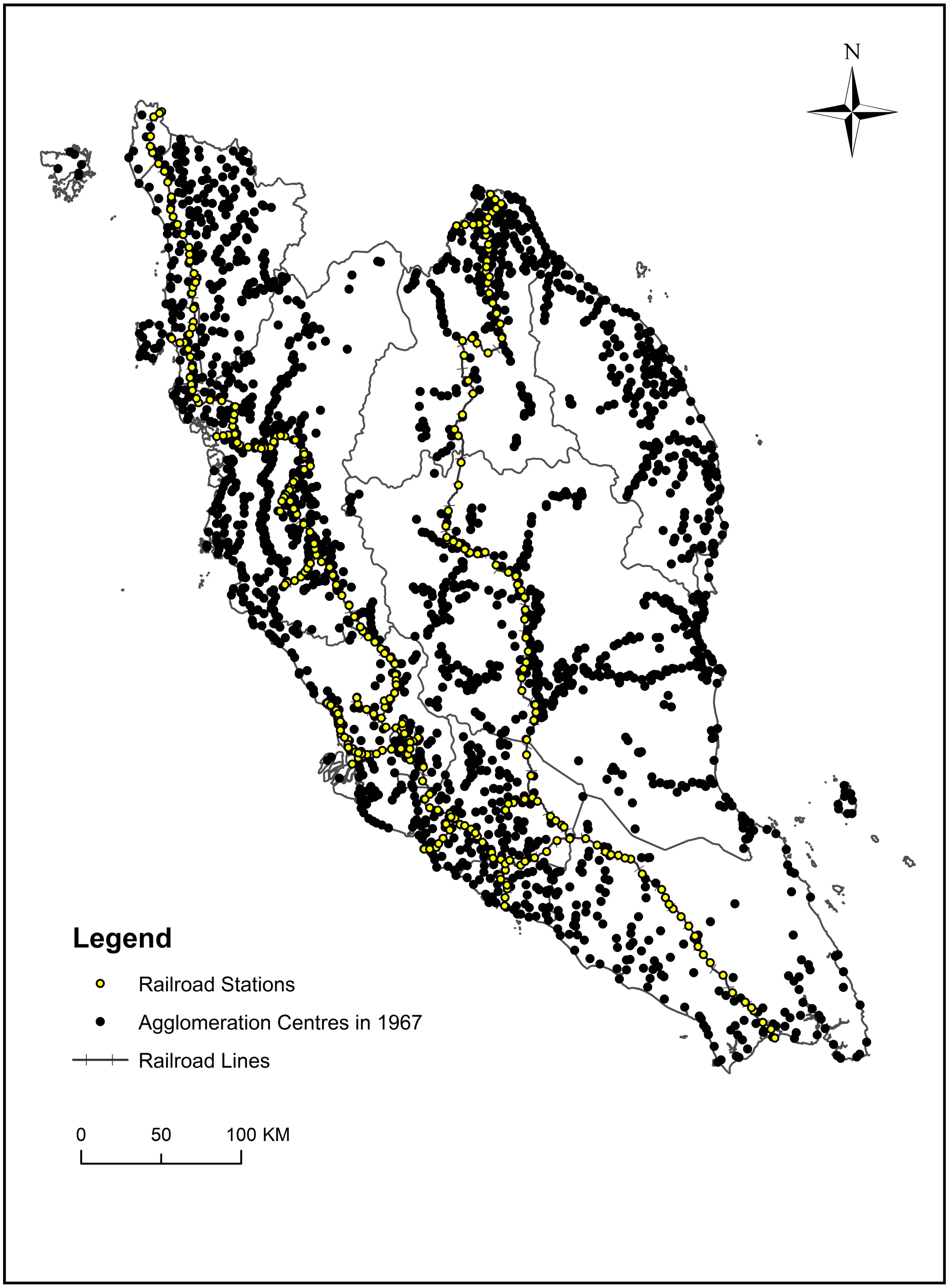
The construction of neighboring cells is shown in the Figure A11 below. The blue points represent the original railroad stations, while the red points denote railroad stations 20 km away from the east and west—neighboring cells. Therefore, we are capturing the effect of the original railroad stations on neighboring cells 20 km from the east and west. However, the shift of the original railroad stations 20 km to the west has made the top left corner of the neighboring cells fall outside the boundary of Malaysia. Therefore, for this stretch of railroad stations, we could only measure the impact on the eastern direction. Similar data constructions and analyses are conducted for distances of 3 km, 5 km, 10 km, 15 km, and 25 km.

We stopped at 25 km for two reasons. First, the gap between the east and west-coast lines are not large; any distance farther than 25 km would indicate that we may be capturing the effect of rail stations from the other rail line. Second, a considerable part of the west-coast line is located near the coastal area. Hence, any cells farther than 25 km from the west-coast line is indeed an ocean. Additionally, neighboring cells farther than 25 km from the eastern side consist of a large portion of stations located in the west-coast line.

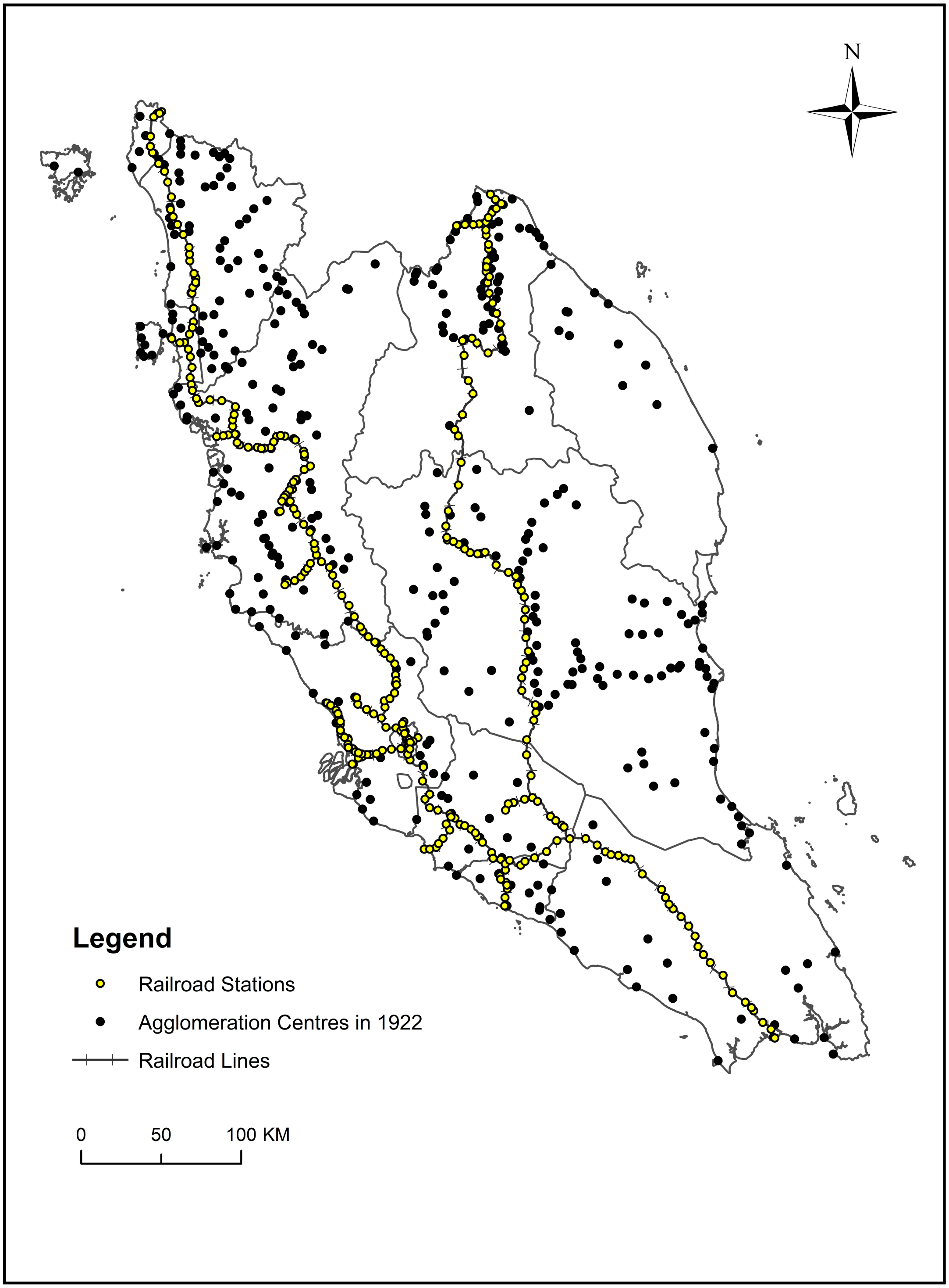
Figure A11: Neighbouring Cells of Railroad Stations



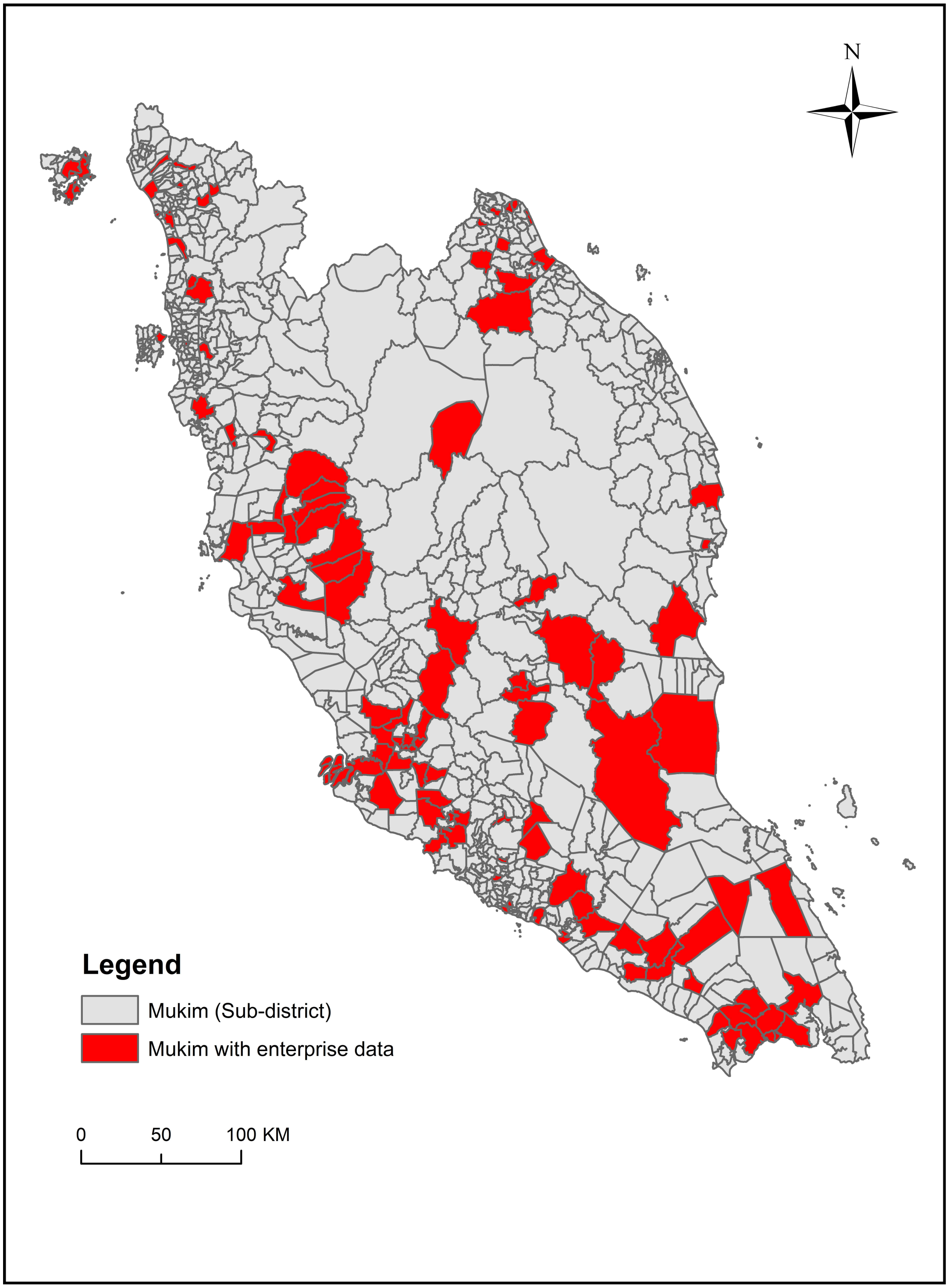
Appendix A12: 1967 Agglomeration Centres



Appendix A13: 1922 Agglomeration Centres



Appendix A14: Mukims with enterprise data



Appendix A15: Relative importance of each channel

We included extra control of agglomeration centers and population into our benchmark analysis in attempt to understand the relative importance of each mechanism. In column 1 of Table A15, we first include control for dummy of agglomeration centers in 1967. The coefficient for railroad stations drops slightly by 2% to 8.97 from our benchmark results of 9.15. In column 2–3, similarly as our 2SLS-IV estimation, we control for the number of agglomeration center in 1967 and change in agglomeration center from 1922 to 1967. Likewise, the coefficients of railroad stations fall by roughly 3%. These results suggest the effect of railroad stations on agglomeration center in 1967 is relatively small.

Next, we account for population in year 2000, the earliest date where data is available. Hence, we use night lights intensity in year 2013 as the outcome variable. Column 4 of Table A15 shows the result before controlling for population while column 5 shows the coefficient after we account for population in year 2000. The size of the coefficient drops significantly by more than 60%. This implies that change in population is the major mechanism in which railroad station affects economic activity in the long term.

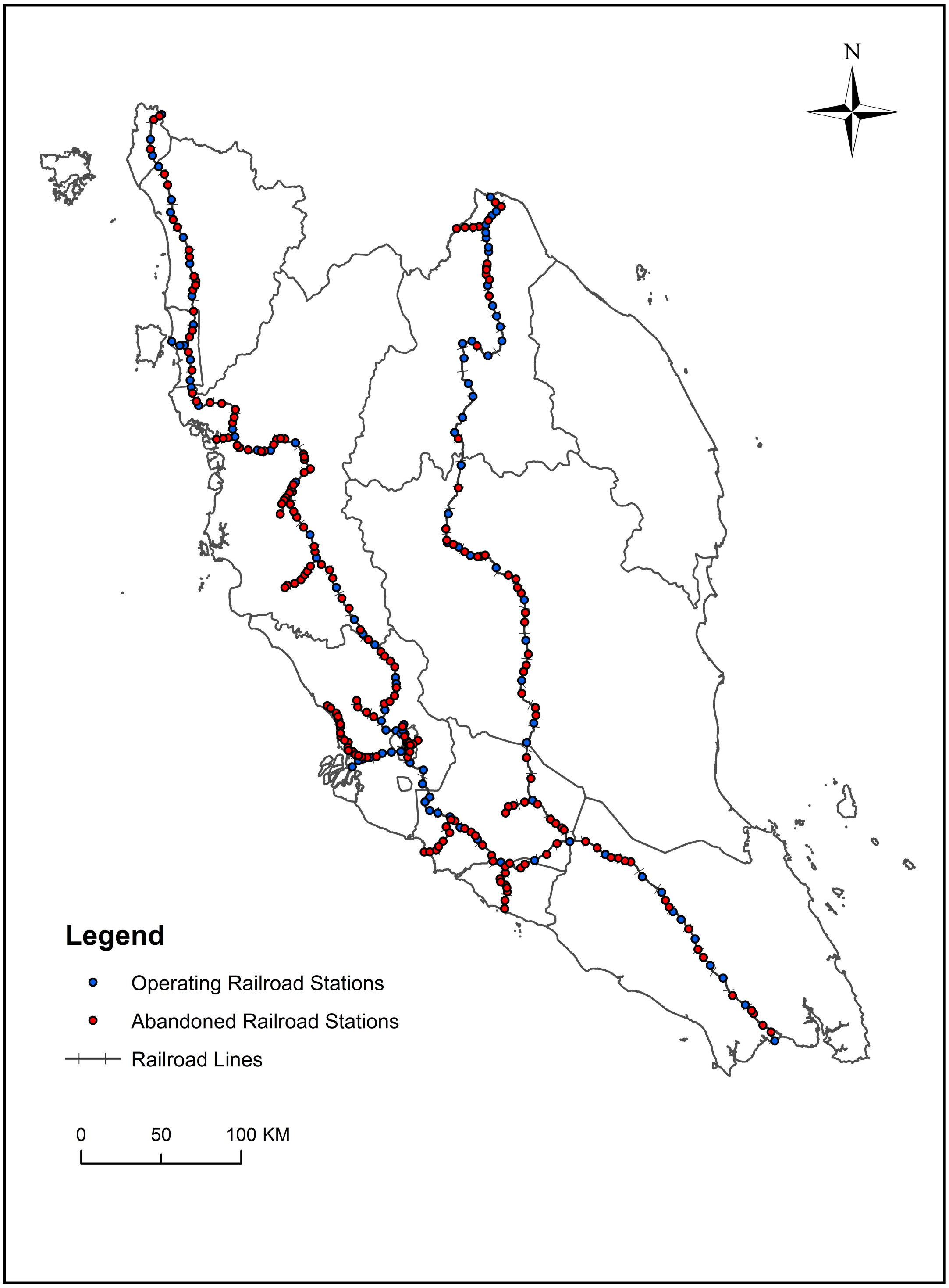
In column 6, we control both population and agglomeration together and the coefficient falls slightly compare to column 5. Taken together, these result suggests that population change is the major channel in which railroad station affects economic activity in the long term. As agglomeration benefit from railroad stations will be accumulated over time as we have shown in Figure 5, the relatively low effect of agglomeration centers in year 1967 could be solely due to the shorter time period of railroad station access.

Table A15: Relative importance of each channel

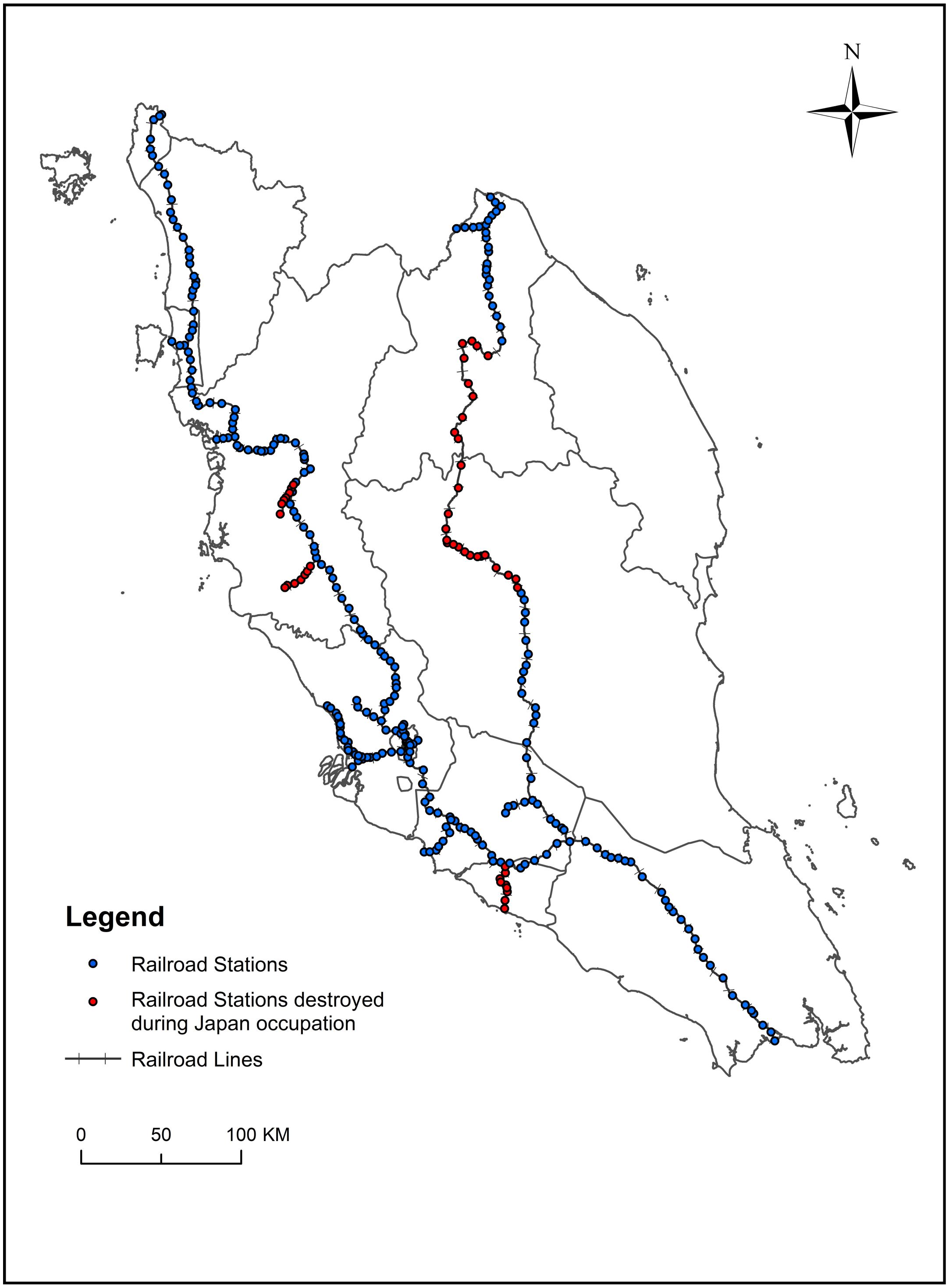
Dependent Variables:	Average Digital Number (DN), 1992–1994			Digital Number (DN), 2013		
	(1)	(2)	(3)	(4)	(5)	(6)
Station access by 1931	8.97***	8.85***	8.90***	15.2***	5.67***	5.46***
	(1.655)	(1.668)	(1.673)	(1.897)	(1.541)	(1.488)
Dummy for agglomeration center, 1967	1.67***					
	(0.487)					
Number of agglomeration center, 1967		0.57***				
		(0.138)				
Change in agglomeration center, 1922–1967			0.59***			1.36***
			(0.141)			(0.209)
Population, 2000					0.020***	0.019***
					(0.004)	(0.004)
Observations	107072	107072	107072	107072	107072	107072
R^2	0.26	0.27	0.27	0.41	0.59	0.61

Note: This table shows OLS estimates regressing average DN for 1992-1994 on historical railroad station access at 1 km^2 cell. Controls include dummy for agglomeration centre in 1967, number of agglomeration centre in 1967 and change in number of agglomeration centre 1922–1967, population in 2000, river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. In parentheses are the robust standard error clustered at the district level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Appendix A16: Operating and Abandoned Stations



Appendix A17: Stations destroyed during Japan occupation



Appendix A18: Hamornised Night Lights Data

	Dependent Variable: Average Digital Number (DN), 1992–1994						
	Peninsular Malaysia	Phase 1	Phase 2	Phase 3	West coast	East coast	Truncated Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Station access by 1931	8.06***	13.3***	10.7***	4.93***	9.64***	2.20*	0.90***
	(1.524)	(4.177)	(2.112)	(1.446)	(1.725)	(1.058)	(0.315)
Observations	107072	106821	106851	106930	55091	51981	2546
R2	0.28	0.28	0.28	0.28	0.30	0.075	0.40

Note: Using the "Cell Approach" at 1 km^2 level, this table shows OLS estimates regressing average night lights intensity (in DN) for 1992-1994 on the access to historical rail stations. Controls include river dummy, coastline dummy, log of topography ruggedness, tin mining area, rubber cultivation area and state dummy. In parentheses are the robust standard error clustered at the district level. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.