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SPECIAL ISSUE PAPER

Can air traffic booms induce innovation and bridge regional innovation gaps?

Inggrid[1] · Budy P. Resosudarmo[1]

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Abstract
The key role of innovation in long-term economic growth is well-established, but it is unevenly distributed across regions. This paper examines how increased air passenger traffic fosters innovation and whether it reduces innovation disparities. Focusing on regional innovation in Indonesia, measured by patent activity, we utilize the exogenous airline deregulation in the early 2000s, which significantly boosted domestic air passenger traffic. Using a newly geocoded patent dataset for Indonesian municipalities from 1995 to 2016, we find that domestic air passenger traffic positively affects regional patenting. This result is robust across various samples and sensitivity tests. However, increased air passenger traffic alone may not suffice to reduce innovation disparities within the country.

JEL Classification O18 · O31 · R12

1 Introduction

The notion that innovation is a key ingredient of long-term economic growth is well established (Romer 1990; Grossman and Helpman 1994; Jones 1995 and 2002). Intriguingly, this hypothesis has spurred urban economists to better understand the geography of innovation within a country. To date, there is broad consensus on the central role of cities in innovation, as they attract high-skilled talents who benefit from dense learning environments and ultimately foster the creation of new ideas (Glaeser 2000). Consequently, the number of innovations and innovative activities varies significantly across different regions within a country. For example, a study by the Brookings Institution found that in the USA, just five top innovation metro

✉ Budy P. Resosudarmo
budy.resosudarmo@anu.edu.au

Inggrid
Inggrid.Inggrid@anu.edu.au

1 Arndt-Corden Department of Economics, Australian National University, Canberra, ACT 2601, Australia

areas—Boston, San Francisco, San Jose, Seattle, and San Diego—accounted for more than 90% of the nation's innovation-sector growth from 2005 to 2017. As a result, the US innovation industry has become heavily concentrated in just a few places. One-third of the nation's innovation jobs now reside in just 16 counties, and more than half are concentrated in 41 counties (Atkinson et al 2019).

Similarly, a study by the Organisation for Economic Co-operation and Development (OECD) found that patenting activity and research and development (R&D) spending are highly concentrated. Ten large regions account for about 45% of global patents and private sector spending on R&D among 34 OECD countries with available data. The same 10 regions produce a sizeable share (approximately 18%) of OECD-wide gross domestic product (GDP) but far less than their contribution to frontier innovation. The report further argues that this does not mean there is no frontier research activity elsewhere: many regions have frontier activities in certain sectors or academic disciplines. It does, however, mean that a purely frontier-focused approach to innovation policy will exclude many places, firms and people and will miss out on their potential (OECD, 2020).

These findings confirm that innovation activities are not evenly distributed across regions and that there are significant disparities in the level and types of innovative activities taking place in different geographic areas. These disparities can have significant implications for regional competitiveness, economic growth and development, and as argued in the new growth theory which has drawn its attention to the study of ideas as a key ingredient of long-run economic growth. These ideas are that they are non-rivalrous by nature, and their formation depends crucially on the stock of critical researchers and strong inventors who responds to economic incentives in the market (Romer 1990, Grossman and Helpman 1994, and Jones 1995, 2002).

Strong inventors might not be equally distributed across the world. However, certain environments allow inventors to improve their productivity through external learning sources (e.g., learning by doing, personal experience, and individual discovery) and endogenous interactions with others. As Stephan (2012) stressed, the most valuable knowledge is often tacit and requires thorough contact and continuous interactions. Akcigit et al. (2018) demonstrated that reducing the cost of interactions can enhance the quality of innovation. Co-locating inventors helps them build their knowledge over time through direct learning, interactions, and collaborations, thus bolstering the production of ideas (Lucas, 1988; Akcigit et al., 2018). One key policy implication from this innovation literature is the importance of lowering search costs (e.g., transport infrastructure) for finding learning sources and interacting with others.

This paper first aims to shed light on how a more conducive environment for searching, induced by an increase in air passenger traffic, stimulates innovation. We argue that the decline in search costs following airline reform enhances physical and geographical proximity among inventors. Second, this paper examines whether the increase in air passenger traffic reduces innovation disparities.

This paper utilizes the case of Indonesia to achieve its objectives for at least three compelling reasons. Firstly, despite being the fourth most populous country globally, Indonesia's innovation outcomes have been rather underwhelming when compared to its peers. According to the Global Innovation Index (GII), Indonesia's innovation performance has consistently lagged just behind that of the three other 'tiger cubs economies' (i.e., Malaysia, Vietnam, and Thailand) between 2012 and 2018 (Fig. A1 in Appendix A).

Second, looking deeper into sub-national innovation data, we observe striking regional variations in innovation across Indonesian cities. In 2000, innovation activity was highly concentrated in Javanese cities, although it gradually diminished in subsequent years.[1] Thirdly, Indonesia stands out as the world's largest archipelago nation, and it is widely recognized that underdevelopment of inter-island transportation infrastructure has hindered the country's economic growth (Hill et al. 2008). For this reason, in the early 2000s, a significant airline deregulation initiative was introduced with the aim of improving inter-island transportation within the country. As a result, domestic air passenger traffic increased. Therefore, this paper seizes upon the exogenous airline deregulation as an ideal opportunity to study the causal impact of increased airline traffic on regional innovation.

Fourth, recognizing that well-functioning transportation systems are a primary determinant of economic development, the government of Indonesia has recently budgeted over USD 400 billion (6.1% of GDP) to boost national infrastructure from 2020 to 2024. As expected, the largest share of planned investments in national infrastructure (60% of the total) has been allocated to the transport sector, including an ambitious plan to construct more than 20 new airports throughout the country (BAPPENAS 2020). Therefore, having evidence of the positive effects of improved transport services will provide further justification for adopting such significant policies.

Our empirical analyses are based on newly assembled city-level data on patenting—a proxy for innovation—domestic air travel, and other related variables, covering the period from 1995 to 2016. Our main finding is that an increase in domestic passenger air traffic in a city induces an increase in the number of patents in that city. Additionally, the heterogeneity analysis reveals stronger effects of air travel on Java Island, significant innovation, government-produced innovation, and innovation from cities served by primary hub airports, which are typically in areas of higher development. Hence, there is an indication that increasing domestic air traffic alone might not address innovation disparities in the country.

This research relates to several strands of literature. Firstly, our paper is part of the literature showing the impact of transport infrastructure on innovation. Using data from developed countries, several studies have demonstrated the positive effects of railroads and roads on regional innovation (Andersson et al. 2023; Agrawal et al., 2017; Perlman 2015). In particular, this paper complements the limited literature documenting the importance of air transport in reducing spatial friction in the market for innovation. An example is the study by Hovhannisyan and Keller (2015), which shows how the inflow of cross-border business travelers from the USA is associated with an increased number of patents in foreign countries. Our paper extends this existing literature by exploring whether transport infrastructure development can reduce innovation gaps within regions. Second, our paper relates to

[1] See, Figures A2 and A3 in Appendix A for details.

the literature on the origins of innovation disparities within a country (Agrawal et al. 2017; Babina et al. 2023; Bell et al. 2018; Berkes & Nencka 2024; Roche 2020). Finally, this paper adds to the debate on the substitutability of air travel and internet access (Agrawal and Goldfarb 2008; Forman et al 2015, 2016; Forman and van Zeebroeck 2012).

The remainder of this paper is organized as follows. In Sect. 2, we describe the institutional background of airline deregulation in Indonesia, which serves as the backdrop for our study. This is followed by a section detailing the construction of the innovation measure and other variables utilized in the empirical analysis. Section 4 discusses the empirical strategy and various challenges to obtain a credible estimate of the air service effect. Section 5 presents the main results, sensitivity checks, and heterogeneity analyses. The final section concludes.

2 Institutional setting: Indonesia's airline deregulation in 2000s

This section provides an overview of Indonesia's experience with airline deregulation in the early 2000s, which served as an exogenous policy experiment that successfully transformed the aviation industry. Before the liberalization period, the domestic airline industry exhibited characteristics akin to an oligopoly, marked by significant market concentration and the establishment of formidable legal barriers to entry. These barriers were primarily implemented to shield incumbent airlines from new competitors.[2] The Indonesian Ministry of Transport held complete responsibility for issuing entry-exit permits and allocating flight routes to carriers, while the Indonesian National Air Carrier Association (INACA) possessed the authority to establish pricing mechanisms (Direktorat Jenderal Perhubungan Udara 2005).

Regulatory reform of the avian industry occurred following the 1997/98 Asian Financial Crisis (AFC). The primary objective was to foster a healthy aviation industry by eliminating any practices that hindered or distorted free competition.[3] The de facto airline liberalization itself began in earnest during the last months of 1999, when the government issued permits for scheduled air services to four low-cost carriers (LCCs).[4] However, the linchpin of these policy changes was the enactment of the Airline Deregulation in 2001, which eased the entry requirements for setting up an airline company in the country. As summarized in Table 1, the deregulation

[2] At that time, the market consisted of only six players: two prominent state-owned enterprises, namely PT Garuda Indonesia Airways and PT Merpati Nusantara Airlines, along with four small private enterprises, namely PT Bouraq Airlines, PT Mandala Airlines, PT Dirgantara Air Service, and PT Sempati Air. However, it's noteworthy that PT Sempati Air filed for insolvency and ceased operations in the middle of 1998.

[3] In alignment with the Memorandum of Economic and Financial Policies, a law known as the Law on Prohibition of Monopoly Practices and Unfair Business Competition (Law No. 5/1999) was enacted during the first quarter of 1999. Subsequently, in the following year, the new commission for business competition, referred to as the *Komisi Pengawas Persaingan Usaha* (KPPU or Business Competition Supervisory Commission), was established to oversee and enforce the provisions of this law.

[4] The two notable operators among them were: (i) PT Air Wagon International (AWAIR) established by the former President Abdurrahman Wahid and currently known as PT Indonesia AirAsia after the acquisition from AirAsia Berhad, and (ii) PT Lion Mentari Airlines which has dominated the domestic

specifically targeted two key aspects of the industry. First, while the old regulatory regime strictly restricted airline ownership to limited companies, the Ministerial Decree in 2001 allowed all legal business entities, including sole proprietorships and cooperatives, to own airlines. Second, since 2001, new entrants could obtain a scheduled air service license for both domestic and international flights without holding a non-scheduled domestic air license for the previous five years as long as they operated at least 2 aircraft (the former requirement was to operate 5 aircraft) (Anas and Findlay 2017).

The immediate effects of the 2001 deregulation on the airline industry are noticeable in the data. During the first three years after deregulation, the number of scheduled airlines and the number of city-pair routes were approximately twice their number in 1999. Price competition among domestic airlines was prevalent and caused further reductions in domestic airfares (Direktorat Jenderal Perhubungan Udara 2005). As a result, the number of domestic passengers increased rapidly after 2001, although it began to recover following the entry of new LCCs in 1999. It is further observed that small airports were mostly affected by the bust and boom in domestic air travel. Over the years, we can see that the 2001 deregulation had large and persistent effects on the increase in air passenger traffic with small airports benefiting the most (Fig. 1).

Finally, there is no systematic documentation indicating that the introduction of the 2001 airline deregulation was intended to shift the direction of innovation. Despite a short contraction in 2002–2003, the time series of regional innovation, measured by the number of patents, virtually exhibited an upward trend during the period 1995–2016 (Fig. 2). This assures us that the deregulation package was exogenously imposed, thereby providing a unique opportunity to alleviate many endogeneity concerns in establishing the causal effect of improved air services on innovation.

3 Data

In this paper, we merge individual patent application data with airport-level information, including the number of domestic air passengers and various city (*kota*) covariates. As a result, we work with an unbalanced panel dataset encompassing Indonesian cities for the years 1995–2016. We outline the main variables used in the analysis below.

Footnote 4 (continued)

aviation market in recent years. The remaining carriers were PT Bayu Air Indonesia and PT Indonesian Airlines. Three more licenses were awarded to PT Jatayu Airlines, PT Star Air, and PT Pelita Air Service in 2000. Until now, only PT Pelita Air Service has survived in the market.

Table 1 Major changes in the aviation industry after the 2001 airline deregulation

	Before deregulation	After deregulation
Ownership	A private limited company or a public limited company	All legal business entities, including a sole proprietorship and a cooperative
License	A non-scheduled domestic air service license (5 years) prior to be eligible for a scheduled (domestic and international) air service license Operating at least 5 aircraft	Possible to directly apply for a scheduled (domestic and international) air service license Operating at least 2 aircraft

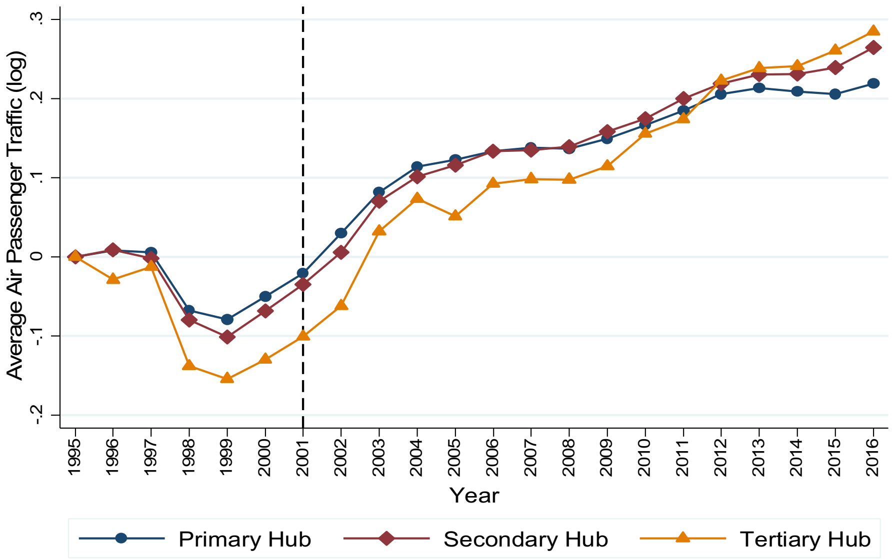

Fig. 1 Trends in Air Passenger Traffic by Airport Size. All figures are normalized using the year of 1995 as the reference point

3.1 Innovation

The innovation outcome of patent counts is obtained from the Directorate General of Intellectual Property Rights (DJKI), the Ministry of Law and Human Rights (*Kemenkumham*). Two potential variables are traditionally used to measure the innovation activity of a region: domestic patent applications and granted patents. We focus primarily on domestic patent applications with interim completion as a minimum and therefore awarded filling dates. This preferred measure of innovation not only reflects a timely innovation in a given year, but also enables us to avoid truncation problems because of the time lag between application and granting dates which is between 3 and 6 years in our case.

For every patent, DJKI provides detailed information on the filling and granting dates, the number of claims, patent types, and one or more technology categories of the International Patent Classification (IPC) to which it pertains. Each application also records the identity and exact location of the assignees (i.e., an individual, a company, an academic institution, or a research institute) that owns the legal rights to the patent once granted. We then associate a patent with the city of the first assignee.

3.2 Air traffic

The key independent variable of interest is the total number of domestic air passenger arrivals and departures at the airport level, provided by DGCA. This means that

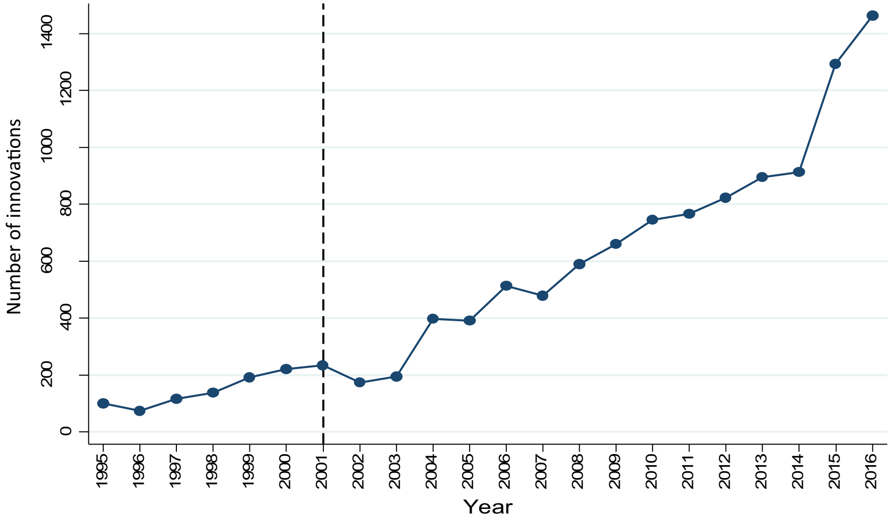

Fig. 2 Trend in Innovation

we assume equal contributions from both inflows and outflows of air passengers to patenting. Our rough measure of intra-national mobility of people also encapsulates all relevant purposes of traveling (i.e., flying for business, education, leisure, and others) and cannot isolate a particular type of trips that are not primarily related to any invention activities, such as traveling to visit family or friends. Another point to highlight is the restriction of the sample to scheduled air services at Indonesian hub airports. For an obvious explanation, hub airports offer nationwide services coverage. Importantly, however, they are popular among time-sensitive travelers (i.e., those who travel for business and other professional motives), and this noticeably helps us to minimize measurement errors due to the very broad measure of air passengers.

To find the number of air passenger flows for each city, we calculate the geodetic distance between the geographic coordinates of the centroid of a city and its nearest airport. The computation results indicate that, on average, it takes approximately 60 km (km) for a resident in a city to reach the nearest airport. Unsurprisingly, this estimated distance is definitely within the catchment areas of all hub airports as stated in Ministerial Decree No. 69/2013 (Ministry of Transportation 2013), except for the case of Bali Island and a few areas of Eastern Indonesia.[5]

[5] The regulation related to airport catchment areas sets a maximum service distance of 100 km for Sumatra and Java, 60 km for Kalimantan and Sulawesi, and 30 km for Bali, Nusa Tenggara, Maluku, and Papua.

3.3 Control variables

Our control variables encompass a set of explanatory factors commonly associated with an innovation production function. The primary source for these main covariates is the Indonesian Central Bureau of Statistics (BPS). The first variable considers human capital input, represented by the percentage of the population that has completed tertiary education. Additionally, we incorporate the share of the labor force engaged in both the manufacturing and services sectors, which reflects the significance of the economic structure and productive resources within each municipality. Data for these three variables are derived from the national socio-economic survey (SUSENAS) datasets provided by BPS. Another essential statistic from BPS is the annual mid-year population estimates, which depict urban agglomeration trends.

To augment our fundamental innovation inputs, we incorporate data on the number of universities from the Directorate General of Higher Education (DIKTI), given the absence of research and development (R&D) spending data. Additionally, to account for both domestic and international technology transfers, we factor in the values of domestic investment (DI) inflows and foreign direct investment (FDI) inflows. These data sources are obtained from the Indonesian Investment Coordinating Board (BKPM).

Table 2 presents summary statistics of the patent application counts along with the other main variables used in the analysis. This table tells us that, in general, variations in the control variables are largely attributed to variations across cities. Hence, all these figures suggest the suitability of a city fixed-effects specification when estimating our innovation model.

4 Empirical strategy

As discussed above, our main interest in this paper is to test whether the air traffic boom induced by the airline liberalization promotes regional innovation. The main empirical specification is the following fixed-effects model:

$$\ln\left(\mathrm{E}\left[A_{kt}|P_{kt}\right]\right) = \alpha + \beta \ln P_{kt} + \gamma X_{kt} + \eta_k + \delta_t + \varepsilon_{kt} \tag{1}$$

where A_{kt} denotes the expected number of patent applications in city k in year t. P_{kt} measures the volume of domestic air passenger traffic.[6] Thus, β is the coefficient of interest, reflecting the effect of air passenger traffic on innovation. X_{kt} is a vector of time-variant control variables as described in the Data section. η_k is city fixed effects to control for unobservable time-invariant heterogeneity across cities. The inclusion of year fixed effects, δ_t, is to account for aggregate macroeconomic shocks that uniformly affect Indonesian cities. The error term, ε_{kt}, captures other relevant time-varying unobservable shocks to the outcome of interest. The main identifying assumption in this fixed effects regression is that: no-unobservable factors of patenting that

[6] Starting now, air passenger traffic refers to domestic air passenger traffic.

Table 2 Summary statistics for the main variables

Variable	Mean	S.D	Min	Max	Obs
Number of patents	4.583	12.814	0.000	153.000	1844
Air passengers (log)	6.199	0.672	3.941	7.645	1844
Number of universities	0.016	0.011	0.000	0.119	1781
University education (%)	9.328	4.122	0.214	28.348	1844
Employment in manufacturing (%)	19.788	8.248	3.250	59.559	1844
Employment in services (%)	66.384	13.321	15.048	90.902	1844
Foreign Direct Investment (FDI) (log)	0.234	0.853	0.000	5.801	1841
Domestic Investment (DI) (log)	1.143	2.744	0.000	9.574	1841
Population (log)	5.472	0.445	4.394	6.458	1781

Domestic and foreign direct investments are converted in constant 2010 using implicit price deflators of gross regional domestic product (GRDP)

correlate with both air traffic and innovation after conditioning on our observable city covariates and the time-invariant city characteristics. In practice, we employ a Negative Binomial (NB) regression algorithm to estimate our patent counts model because we find strong evidence of over-dispersion in the patent dataset.[7] We allow bootstrapped standard errors (100 replications) correlated over time within each city to account for the plausibility of serial correlation in patenting.

To check the robustness of the result from the main empirical specification, we conduct several robustness tests. The first robustness test addresses the major challenge of estimating β, which is endogeneity biases due to the non-randomness of air passenger traffic. A study by Akcigit et al. (2017), for example, indicates that US inventors sort themselves across dense urban areas to facilitate their human capital accumulation, have access to well-developed financial institutions and wider geographical connectivity, and expand the market size of their innovations. Resembling these findings, a possible case of self-selection in this study is that inventors are keen to fly to prospective places for innovation, and hence this flow of talents will foster innovation in the respective regions. In the same vein, we need to consider the plausibility of unobserved variables that simultaneously affect innovation and air passenger traffic. One conjecture is that regional economic growth not only expands local innovation but also leads more people to fly.

We utilize a standard control function (CF) technique to address the endogeneity of air passenger traffic.[8] To construct our control function, we first estimate an air passenger traffic regression below:

[7] Another option is to use a Poisson regression estimator. However, the validity of statistical inferences based on this method hinges on the assumption of equi-dispersion which is clearly violated in our case (Cameron and Trivedi 2013).

[8] Instead of employing an instrumental variable (IV) strategy, we use a control function approach because it can parsimoniously handle our high dimension fixed effects models.

$$\ln P_{kt} = \alpha_0 + \theta\left(\ln D_k \times CPI_t\right) + \gamma_0\prime X_{kt} + \mu_k + \lambda_t + \upsilon_{kt} \tag{2}$$

where D_k is the minimum distance from city k to its closest airport and CPI_t is the national consumer price index in year t. This interaction term, therefore, reflects the lowest distance costs to the nearest airport. We expect an inverse relationship between air passenger traffic and distance costs. The validity of the distance costs requires two conditions here: the costs strongly correlate with the air passenger traffic and can only affect patenting through the air service.

We then add the CF $\widehat{v_{kt}}$, the predicted residuals υ_{kt}, to Eq. (1) as follows:

$$\ln\left(\mathrm{E}\left[A_{kt}|P_{kt}, \widehat{v_{kt}}\right]\right) = \alpha + \beta \ln P_{kt} + \gamma' X_{kt} + \eta_k + \delta_t + \varphi\widehat{v_{kt}} + \varepsilon_{kt} \tag{3}$$

The β coefficient obtained from Eq. (3) will be consistent because the CF $\widehat{v_{kt}}$ is able to purge the correlation between the air passenger traffic and the error term. This equation also allows us to test the null of exogenous air passenger traffic, $\mathrm{H}_0 : \varphi = 0$(Wooldridge 2010).

The second robustness test deal with the limitations associated with using the number of patent applications as the sole indicator of innovation output. In line with the insights of Griliches (1990), aggregate patent counts fail to capture the significant variations in the technological and market value of innovations. Market trends often reveal a multitude of patents that bring only marginal improvements, resulting in relatively modest economic value, while a select few are recognized as high-value inventions.

To address this limitation, we take advantage of the availability of patent claims to enhance the robustness of our analysis. Similar to other measures of patent quality, each claim represents a novel contribution of the invention to a specific technical domain. This implies that patents with a greater number of claims tend to be more valuable and can yield higher profits. In summary, patent claims hold equal importance to both forward and backward patent citations when constructing a composite index for patent quality (Lanjouw and Schankerman 2004).

In the third robustness check, following the existing literature on the importance of population density for innovation (Carlino et al. 2007; Feldman and Audretsch 1999; Rosero et al. 2020), we replace our population variable with population density to determine whether size or density is a more appropriate control for urban agglomeration trends. The fourth robustness check addresses any possible omitted variable bias. While our city fixed effects can rule out all biases from time-invariant characteristics that have been found to be important predictors of regional innovation, there is still a notable concern regarding the presence of time-variant confounders that are simultaneously correlated with innovation and air passenger traffic.[9] Chief among these is the long-lasting effect of the Asian Financial Crisis (AFC)

[9] For example, Gorodnichenko and Roland (2011), who pay attention to cultural attributes, show that societies placing a high value on personal freedom and status are positively associated with growth and innovation. Regional openness to creativity and diversity is not only attractive to inventors but also encourages high-technology industries and higher regional income per capita (Florida 2002).

in 1997/1998. To address this potential confounder, we drop the observations from 1997 to 1998 and repeat the regression estimations.

We also experiment with two additional time-varying control variables to reduce the bias from omitting relevant variables in the analysis. Specifically, we control for the level of economic development across cities by including regional GDP per capita and the incidence of poverty.[10] We furthermore include technology classification fixed effects and island-year fixed effects to verify that our results are robust to unobserved heterogeneity bias arising from variations in patenting across technological fields and inter-island heterogeneity.

In the fifth robustness test, we use lagged values of the patent variable as regressors. One advantage of utilizing a panel dataset is its capability to capture the process of knowledge accumulation, where previous knowledge serves as inputs for future knowledge (Aghion and Howitt 1992). Important for our identification strategy as well, this specification allows us to resolve the reverse causality issue as explained previously.[11]

To provide additional validation of our research design, we perform a placebo analysis in our air passenger traffic variable. The idea of this test is to replace our original air passenger traffic measure with air passengers in transit. We believe that the number of transfer passengers is an arguably appropriate placebo for two reasons. Intuitively, this variable is a strong predictor of arriving and departing passengers. We also argue that passenger arrivals and departures are the only route through which transit passengers affect patent applications, such that it is very unlikely for inventors in transit to apply for patents in their transit places.

5 Results

5.1 Main results

Table 3 presents the main findings from the regression of air passenger traffic on patent counts. We divide the table into three parts: the first part displays the results from the pool model, the middle part shows the findings from the city fixed effects, and the last part is the estimated coefficients from city-year fixed effects.[12] All estimates of β given in Table 3 reveal a positive and statistically significant impact of air passenger traffic on regional patenting activity. As we control for the omitted variable bias in Columns 2, 4, and 6, it is shown that the inclusion of time-varying control variables reduces the magnitude of the point estimates, but they consistently reject the null at the most conservative statistical

[10] Detailed description of these additional control variables can be found in Appendix B.

[11] As is well known, however, this within estimator strategy produces an asymptotic bias in the coefficient estimate as it fails to fulfill the strict exogeneity of the dynamic panel models.

[12] We report the estimated coefficients of the Negative Binomial (NB) instead of the Poisson regressions in all specifications since the former is superior in handling our over-dispersed count data. In our case, the Pearson dispersion test clearly confirms a 98% additional dispersion in the patent data.

significance level. Our preferred or main result, based on the most comprehensive model specification, is presented in Column 6.

Interpreting our results based on the full fixed-effects specification, we find that a 10-percentage point increase in air passenger traffic corresponds to approximately a 5.6% increase in the number of patent applications. For comparison, Hovhannisyan and Keller (2015) observed that foreign patents in the USA increased by 0.2%–0.3% in response to a 10% rise in US outward business travelers during the period 1993–2003. Comparing our findings on air service impacts with those of other transportation modes, Agrawal et al. (2017) estimated an increase in approximately 1.7% in patents for every 10% expansion in interstate highways, based on an examination of US domestic patent data from the 1980s.

We perform a series of robustness analyses to test the validity of the main results. Columns 1–2 of Table 4 display the results of testing the exogeneity of air passengers. Column 1 shows that the cost distance variable enters with a negative sign and is statistically significant in the air traffic regression model. The F-statistic for this variable is also high (378.39) and is significant at the 1% level. These strengthen our argument on the validity of the cost distance variable to control for unobserved factors that are correlated with the air traffic variable. Column 2 of the table presents the findings from an augmented version of the main model by including the estimated residuals from the air service equation. The air traffic coefficient increases little compared to the original specification (5.97% versus 5.58%, respectively) and has a p-value less than 0.01. The statistical insignificance of the CF $\widehat{v_{kt}}$ in this column also better ascertains the presumably exogenous air passenger traffic, providing additional support for the hypothesis that air passenger traffic leads to innovation.

Our second test is to assess the robustness of our definition of innovation. We replace the number of patent applications with the average number of claims per patent in the main model. We show in Column 3 of Table 4 that the finding on the air traffic effect does not change though the magnitude of the estimated air traffic here is somewhat larger than those obtained using the count of patent applications.

Column 4 of Table 4 shows the result of testing whether population density is a better control for urban agglomeration. It can be seen that using population density produces a result similar to our main finding. Therefore, we prefer to continue using population as a control for urban agglomeration in our model. We are next concerned with the potential confounding effects of the Asian Financial Crisis (AFC) during 1997/1998. To investigate this possible confounder, we simply regress the benchmark model excluding the 1997/1998 observations. We note that the corresponding effect on patenting (Column 4) is qualitatively similar to the full sample estimation.

Table 5, specifically Columns 1–3, demonstrates the robustness of our primary findings when considering the inclusion of other time-varying covariates that represent potential omitted confounding factors. We start by removing the proxies for human capital and adding the regional gross domestic product (GRDP) variable in the original model. Now, the coefficient on air services in Column 1 remains positive but slightly decreases to about 4.38%. In Column 2, we incorporate the intensity

Table 3 Effects of air passenger traffic on patent applications

	(1) Pool	(2)	(3) City FEs	(4)	(5) City-Year FEs	(6)
Air passenger traffic	1.133***	0.531***	1.906***	0.918***	1.065***	0.558***
	(0.174)	(0.080)	(0.072)	(0.163)	(0.182)	(0.192)
Number of universities		41.620***		37.519***		33.109***
		(4.921)		(7.835)		(6.958)
University education		0.111***		0.075***		0.012
		(0.018)		(0.017)		(0.017)
Employment in manufacturing		0.034***		0.003		0.036**
		(0.007)		(0.007)		(0.015)
Employment in services		0.003		−0.002		0.030**
		(0.004)		(0.003)		(0.012)
FDI		0.070		0.004		−0.092*
		(0.049)		(0.024)		(0.054)
DI		0.0772***		0.061***		0.052***
		(0.011)		(0.016)		(0.016)
Population		3.409***		1.710***		1.866***
		(0.125)		(0.284)		(0.384)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	No	No	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	Yes	Yes
Observations	1,844	1,781	1,545	1,484	1,545	1,484

The dependent variable is the number of patent applications. Bootstrapped standard errors (100 replications) in parenthesis are clustered at city. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively

of poverty in each city as an additional socio-economic variable. We see the result is still robust to the inclusion of this variable.

Thirdly, we consider the potential role of information and communication technology (ICT) in mediating the relationship between air services and innovation. Initially, it is important to note that the relationship between ICT and face-to-face interactions is not straightforward. On one hand, the advent of advanced information technologies may encourage individuals to rely more on these digital communication methods, thereby reducing in-person interactions. On the other hand, telecommunications can complement face-to-face communications, particularly in scenarios involving the exchange of uncodified and intricate ideas (Gasper and Glaeser 1998).

The most suitable proxy available in this study to gauge the importance of ICT in innovation is the presence of internet access, as provided in the SUSENAS datasets. We calculate the proportion of internet access at the city level using this data. The results, including the ICT variable, are presented in Column 3 of Table 5. Notably, the estimated coefficient for air services remains relatively stable and consistent with the main result. Additionally, we observe positive and statistically significant

Table 4 Robustness checks: endogeneity of air passenger traffic, patent claims, population density and Asian financial crisis

	(1) Air passengers	(2) NB-CF	(3) Claim	(4) Population density	(5) Dropping 97/98
Air passenger traffic		0.597***	0.854***	0.680***	0.558***
		(0.222)	(0.182)	(0.238)	(0.192)
Distance costs	− 0.115**				
	(0.051)				
Constant	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,781	1,484	1,402	1484	1,484

The dependent variable in Column (2), (4) and (5) is the number of patent applications. The dependent variables in Column (1) and (3) are air passenger traffic and average number of claims per patent, respectively. Controls are number of universities, university education, employment in manufacturing, employment in services, FDI, DI and population. Bootstrapped standard errors (100 replications) in parenthesis are clustered at city. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively

contributions of ICT to regional patenting, although these effects are relatively modest.

We further investigate whether ICT serves as a replacement or complement to air transport in fostering innovation. The interaction coefficient between air passenger traffic and internet access is negative and significantly different from zero. Moreover, the joint test of the primary and interaction effects yields statistical significance ($p < 0.000$), suggesting that air services and ICT are not complementary factors when it comes to driving innovation.

In Column 4 of Table 5, we introduce province-specific linear trends in patenting, allowing time trends to vary for each province. Accounting for these linear trends reduces the point estimate of air traffic to just slightly above 0.5% of the main result, with a p-value below 0.01.

Table 5 also addresses various potential sources of unobserved heterogeneity bias stemming from differences in technological fields and samples. When we control for patent class fixed effects (Column 5), the results continue to support the significance of air traffic on patenting. Moreover, the estimated coefficient, which incorporates island-year fixed effects in Column 6, affirms that our findings are not driven by other unusually significant shocks. Therefore, we can conclude that our primary results remain relatively robust, even when considering potential confounding omitted variables.

In Table 6, Columns 1–5, we investigate potential time-lag effects of air services. We evaluate the impact of air passenger traffic at time "t" on patenting over the subsequent five years (t + 1, t + 2, t + 3, t + 4, t + 5). The outcomes presented in these columns highlight significant effects of air passenger traffic on future patenting, particularly within the 1–3 year timeframe.

Table 5 Robustness checks: GRDP, poverty, ICT, provincial trend, patent class and island-year

	(1) GRDP	(2) Poverty	(3) ICT	(4) Provincial Trend	(5) Class FE	(6) Island-Year FE
Air passenger traffic	0.438**	0.377*	0.484**	0.610***	0.198**	0.709***
	(0.208)	(0.195)	(0.228)	(0.168)	(0.101)	(0.160)
ICT			0.079***			
			(0.030)			
Air passenger traffic x ICT			−0.014***			
			(0.004)			
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,484	922	1,418	1,484	11,312	1,484

The dependent variable is the number of patent applications. In Column (1), controls are number of universities, university education, employment in manufacturing, employment in services, FDI, DI and population. In other columns, controls are number of universities, university education, employment in manufacturing, employment in services, FDI, DI and population. Bootstrapped standard errors (100 replications) in parenthesis are clustered at city. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively

Finally, we turn our attention to a common argument that underscores the dynamic nature of innovation, which is reliant on its own past accomplishments. To address this aspect, we add a lagged measure of innovation and re-estimate our model. The estimated coefficient of the lagged innovation is positive and statistically significant at the 10% level, suggesting the importance of previous innovation for future innovation (Column 6 of Table 6). However, the coefficient of interest remains relatively stable.

Our next robustness check focuses on the impact of outliers. While the negative binomial regression is quite effective at handling outliers, we decided to conduct an analysis with influential observations excluded. The outcome in Column 1 of Table 7 reveals that the estimated coefficient for air passenger traffic is slightly larger and significant at the 1% level.

Our final robustness check is to use the number of transfer passengers at airports as a placebo for the volume of arriving and departing passengers. There is a strong relationship between the two variables with the correlation coefficient pointing toward a value of 0.78. The negative and statistically insignificant point estimate for this measure reinforces the causal significance of air passenger traffic on patenting (Column 2 of Table 7).

Table 6 Robustness checks: time-lag effects of air passenger traffic and innovation dynamics

	(1) Patent (t + 1)	(2) Patent (t + 2)	(3) Patent (t + 3)	(4) Patent (t + 4)	(5) Patent (t + 5)	(6) Patent(t-1)
Air passenger traffic	0.433*	0.494**	0.423**	0.350	0.207	0.512***
	(0.225)	(0.216)	(0.215)	(0.242)	(0.180)	(0.195)
Patent (t-1)						0.004*
						(0.002)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,405	1,326	1,237	1,150	1,073	1,418

The dependent variable is the number of patent applications. Controls are number of universities, university education, employment in manufacturing, employment in services, FDI, DI and population. Bootstrapped standard errors (100 replications) in parenthesis are clustered at city. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively

5.2 Heterogeneity analysis

We have demonstrated that the substantial positive effects of air services on patenting in our main model are robust. Nevertheless, these overall estimates might obscure unique impacts of air passenger traffic within specific subgroups. Consequently, we proceed to re-estimate our regression model outlined in Eq. (1) for various subsamples to address these inquiries.

Does a more developed island matter? Java Island, which is generally more developed than other islands in Indonesia, has continued to lead in patenting compared to the Outer Islands (Figures A2 and A3 in Appendix A). To test whether geographic variations in development affect the relationship between air passenger traffic and patenting differently, we split our original sample into two groups: Java and the Outer Islands. As predicted, Table 8 reveals much stronger effects of air passenger traffic on patenting in the more developed island of Java. A 10% increase in air passenger traffic leads to an approximately 7.1% increase in patenting activity on Java (Column 1), whereas the point estimate for the Outer Islands is insignificantly different from zero (Column 2).

How responsive are types of innovation to air passenger traffic? We now seek to gain a deeper understanding of the extent to which air service development impacts more significant inventions. If the premise holds that higher levels of technical inventiveness involve more in-depth and collaborative learning processes, we anticipate a more pronounced role of air services in this category of innovation. Our patent data allows us to make immediate classifications: we distinguish between substantial inventive activities, represented by regular and international (Patent Corporation Treaty or PCT) patents, and smaller, incremental innovations, typically utility model patents. In Columns 3–4 of Table 8, we observe that the impact of air services is notably significant for first-tier patents, with the estimated coefficient

Table 7 Robustness checks: dropping outliers and a placebo

	(1) Dropping outliers	(2) Placebo air traffic
Air passenger traffic	0.648***	
	(0.200)	
Transfer passengers		− 0.019
		(0.049)
Constant	Yes	Yes
Controls	Yes	Yes
City fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	1,462	1,216

The dependent variable is the number of patent applications. Controls are number of universities, university education, employment in manufacturing, employment in services, FDI, DI and population. Bootstrapped standard errors (100 replications) in parenthesis are clustered at city. ***, **,* denote significance at the 1%, 5% and 10% levels, respectively

statistically significant at the 1% level. Furthermore, its magnitude is comparatively higher in relation to second-tier patents.

From a public policy perspective, the greater benefits of transport infrastructure for substantial innovations complement the role of traditional public funding for research and development (R&D) projects. As demonstrated by Beck et al. (2016), R&D subsidy programs in countries like Switzerland have a positive and significant effect on radical innovations but exert no influence on small, incremental innovations. The authors argue that investments in basic and radical innovations are considered highly uncertain, resulting in underinvestment by the private sector in these domains. Consequently, the presence of this market failure underscores the need for public interventions to attain the socially desired level of high-novelty inventions.

Are government agencies still the key actor in the national innovation system? The single largest item of the Indonesian gross domestic expenditure on research and development (GERD) has always been incurred by the public sector. The latest GERD statistics by UNSECO show that approximately 87% of R&D activities were financed by the government in 2016 followed by industry (approximately 7.7%) and unknown sources (approximately 5.3%). In light of this, we expect that the innovation output from government laboratories is more likely to benefit most from the expansion of the air service.

Table 9 provides the regression results from a heterogeneous group of major innovative actors in the national economy. The point estimate for government patenting is almost triple in size compared to individual and firm patenting and statistically significant at the 1% level, reinforcing our argument that the vast majority of publicly funded innovation has the most to do with the air services encouraging co-location and collaboration within and between organizations.

Does a larger airport lead to more innovation? Several studies have highlighted the positive impact of airport size on a range of economic indicators. For

Table 8 Heterogeneous effects: Islands and patent types

	Java	Non-Java	PCT	Utility
	(1)	(2)	(3)	(4)
Air passenger traffic	0.711***	−0.193	0.721***	0.537*
	(0.222)	(0.600)	(0.222)	(0.296)
Constant	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	589	895	1,380	1,257

The dependent variable is the number of patent applications. Controls are number of universities, university education, employment in manufacturing, employment in services, FDI, DI and population. Bootstrapped standard errors (100 replications) in parenthesis are clustered at city. ***, **,* denote significance at the 1%, 5% and 10% levels, respectively

instance, in a sensitivity analysis, Blonigen and Cristea (2015) found that air services positively influence local economic growth even when excluding air traffic data from large hubs, though the effect size is smaller. Sheard (2014), using the number of air passengers as a proxy for airport size, demonstrated that larger airports contribute to a higher employment share in tradable services, with less pronounced effects in non-tradable services. These findings align with the notion that large, urban-based air services play a pivotal role in bolstering tradable services.

Building on these insights, we investigate whether air services exert uniform effects on regional innovation based on airport size. We classify airports into three groups as per the Ministry of Transport's definition: cities served by primary, secondary, and tertiary hubs. Notably, the quantitative impact of air passenger traffic is predominantly driven by the first category of airports. The fixed-effects estimates reveal that the coefficient for the largest hub is nearly five times higher than the main result and statistically significant at the 1% level, whereas the impact on other hubs is marginal (Columns 1–3 of Table 10). Collectively, this analysis provides empirical support for previous research on the connection between robust air service utilization and local economic outcomes, thereby underscoring the potential benefits of airport expansion.

6 Conclusion

In this paper, we study the benefits of air transport development, which is expected to lower inventors' search costs, on regional innovation in Indonesia. We improve on earlier literature regarding the association between innovation and transport infrastructure expansion by employing a more appropriate measure of domestic innovation, based on a newly assembled patent dataset for Indonesia. To establish the causal effect, we argue that the increase in air passenger traffic is due to exogenous air transport policy deregulation in the early 2000s, while

Table 9 Heterogeneous effects by assignees

	Individual (1)	Government Agencies (2)	Firms (3)	Higher Education (4)
Air passenger traffic	0.680***	1.636***	0.643	− 0.023
	(0.233)	(0.571)	(0.999)	(0.639)
Constant	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	1,329	638	785	919

The dependent variable is the number of patent applications. Controls are number of universities, university education, employment in manufacturing, employment in services, FDI, DI and population. Bootstrapped standard errors (100 replications) in parenthesis are clustered at city. ***, **,* denote significance at the 1%, 5% and 10% levels, respectively

controlling for unobservable confounders that simultaneously affect both patenting and air passenger traffic.

Our primary finding suggests that, on average, a 10% increase in domestic air passenger traffic leads to an approximate 5.6% increase in regional patenting. This result remains robust against potential omitted confounding factors, outlier biases, innovation dynamics, and placebo checks. Furthermore, this effect is notably more pronounced on a more developed island, for substantial inventions, among government-dominated actors, and in cities served by primary hubs.

While our findings suggest increased productivity in patenting resulting from air passenger traffic, we have not fully elucidated the specific mechanisms underlying how inventors' matching and interactions operate in practice. First, as Jones (2009) has noted, the accumulation of knowledge tends to demand greater specialization

Table 10 Heterogeneous effects by airport size

	(1) Primary Hubs	(2) Secondary Hubs	(3) Tertiary Hubs
Air passenger traffic	2.400***	0.132	0.1230
	(0.440)	(0.816)	(0.475)
Constant	Yes	Yes	Yes
Controls	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	547	670	372

The dependent variable is the number of patent applications. Controls are number of universities, university education, employment in manufacturing, employment in services, FDI, DI and population. Bootstrapped standard errors (100 replications) in parenthesis are clustered at city. ***, **,* denote significance at the 1%, 5% and 10% levels, respectively and increased collaboration among inventors to address more complex problems in the future. This collaborative work often necessitates long-distance co-operation. We might inquire whether the temporary co-location of inventors induced by air passenger traffic promotes the creation of collaborative patents rather than individual inventions.

Second, our patent dataset lacks sufficient information to address the question of whether the introduction of new flight routes leads inventors to relocate to more promising cities for innovation. Separate research exploring the relationship between regional patenting, inventor migration, and the introduction of domestic flight routes is needed to complement our paper.

In terms of addressing innovation disparities, the heterogeneity analysis in this paper indicates that simply increasing air passenger traffic may not resolve the issue. There is a strong need for traditional development strategies, such as increasing overall development levels, constructing primary hub airports, and increasing government spending on research in regions where innovation levels are still low. Once these regions reach a certain level of innovation, have enough primary hub airports, and sufficient government budgets for research, an increase in air traffic might then help to further boost innovation.

Appendix A

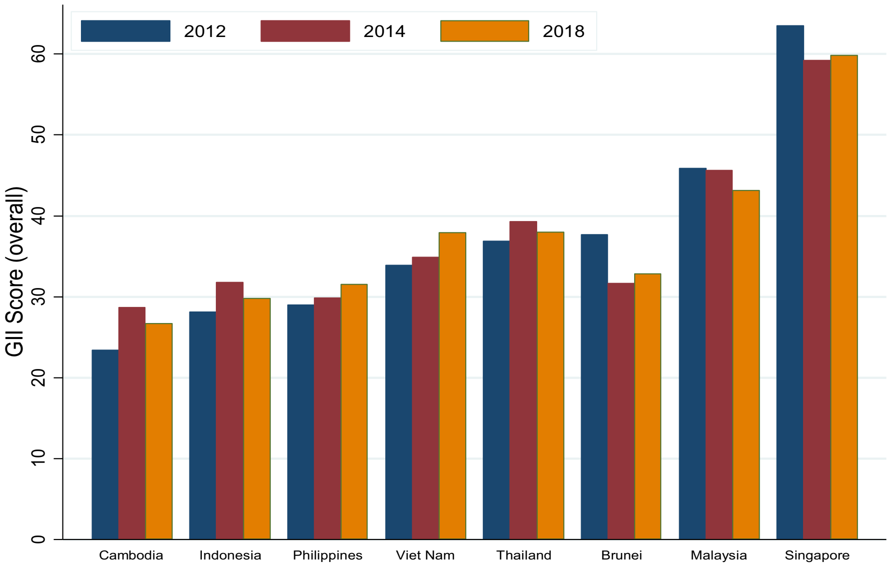

Fig. A1 Innovation output index for ASEAN countries, 2012–2018. Source: Authors's compilation from Global Innovation Index (GII) reports, various years

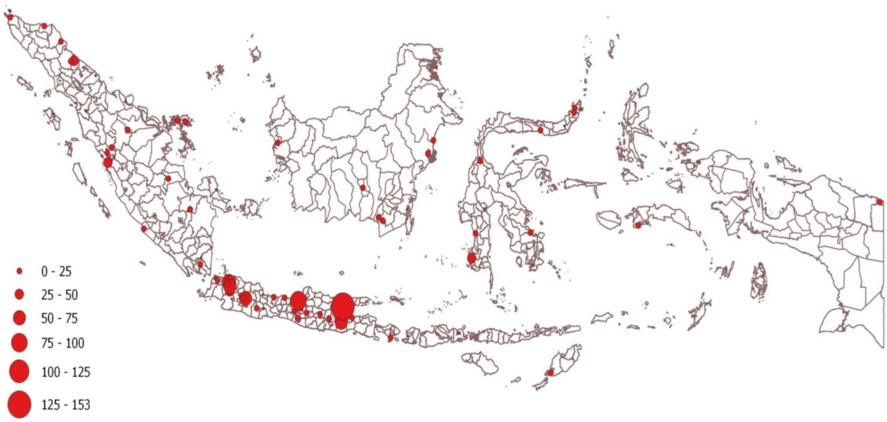

Fig. A2 Geographic distribution of innovation across Indonesian cities in 2016. Innovation is measured by counts of patents

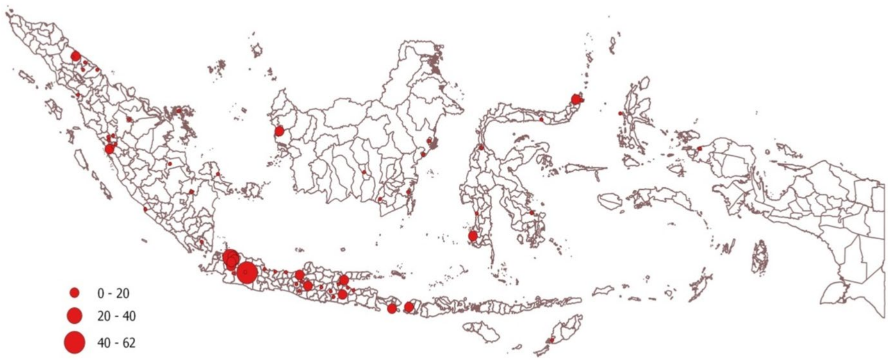

Fig. A3 Geographic distribution of innovation across Indonesian cities in 2000. Innovation is measured by counts of patents

Appendix B Data appendix and variable description

Below we provide a detailed description of the construction of our additional control variables.

- **Information and communication technology (ICT)**: We calculate the share of adult population with access to the internet within the last three months of the survey reference week. The variable is calculated from the National Socio-economic Survey (SUSENAS) by BPS.
- **Urban density**: We construct a measure of population density (the number of population/km^2). Data on population size and total area are taken from the Indonesia Database for Policy and Economic Research (INDO-DAPOER) by the World Bank.

- **Economic output**: The variable of gross regional domestic product (GRDP) is the total GRDP by economic sector at current and constant prices, taken from the Indonesia Database for Policy and Economic Research (INDO-DAPOER) by the World Bank.
- **Poverty**: The variable of poverty represents poverty severity index (P2), taken from the Indonesia Database for Policy and Economic Research (INDO-DAPOER) by the World Bank.

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