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ABSTRACT

ECONOMIC ZONES AND LOCAL INCOME INEQUALITY: EVIDENCE FROM INDONESIA*

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Economic zones can be powerful drivers of economic growth in developing countries. However, less is known about their distributional impact on the local society. This paper provides empirical evidence from Indonesian provinces on the relationship between economic zones and within-province income inequality. Estimates from panel regressions and synthetic control case studies suggest that this relationship is positive overall. The estimated rise in income inequality after a zone opens is relatively small on average and may be short-lived. However, the average estimate masks large regional differences, which suggests that the inequality implications of economic zone policies depend on local conditions. One explanation for the rise in inequality is that the unskilled population benefits disproportionately less from the policy. As a remedy, we propose education and training programs that target the poor and unskilled and in which companies also actively participate.

Keywords: economic zones, place-based policy, income distribution, synthetic control method, Indonesia

JEL classification: D31, F63, O15, O25

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1 Introduction

In his second inaugural speech in December 2019, President of Indonesia Joko Widodo expressed his vision for Indonesia by saying, "[...] our dream, our ambition is that by 2045, after one century of Indonesian independence, Indonesia should, Insya Allah (God willing), have escaped the middle-income trap. Indonesia will have become an advanced country [...]" (The Jakarta Post, 2019)[1] A popular policy tool meant to support the above goal in Indonesia is the establishment of economic zones – two prominent forms of which are industrial estates and, more recently, special economic zones (SEZs). These industrial place-based policies are widely used in developing countries around the world to foster local economic development by attracting foreign investors, creating new employment and helping a country enter global production networks (e.g., Duranton and Venables, 2019).

This paper focuses on the impact of economic zones on one aspect of socio-economic development – income inequality. Economic zone policies in Indonesia are primarily aimed at fostering growth, mainly through industrialization and foreign direct investment, while virtually no attention is paid by policymakers to their distributional impacts. However, it is not unimportant from a developmental perspective how these policies impact local inequalities. Recent literature has shown that the benefits of industrialization and globalization are often not distributed evenly, which can lead to high inequalities and question the social and political sustainability of the growth process (e.g., Kniivila, 2008; Kanbur, 2015; Pavcnik, 2017; Dorn et al., 2018). High income inequality has been shown to correlate with slower long-run growth (Barro, 2000; Berg et al., 2018) and to cause larger macroeconomic volatility and social insecurity (Stiglitz, 2012). Developing countries characterized by high income inequality are also more prone to fall into the middle-income trap (MIT)[2] because the inequality hinders the human capital accumulation process and thus hampers economic productivity and innovation (Wang and Lan, 2017; Paus, 2017; Basri and Putra, 2016).

In this paper, we look at income inequality *within* Indonesian provinces, i.e., our focus is on the local impact.[3] We ask the question of how income inequality in a province responds to the opening of an economic zone in the same province. The empirical analysis is based on

[1]The unofficial English translation of the speech was retrieved from The Jakarta Post: `https://www.thejakartapost.com/news/2019/10/20/the-main-thing-is-not-the-process-but-the-result-jokowis-full-inauguration-speech.html`

[2]MIT refers to the situation when countries experience growth stagnation at middle-income levels, which Gill and Kharas (2007) termed the middle-income trap.

[3]We are aware that economic zones might also influence inequalities between provinces. Indeed, some of them are set up precisely with the aim to promote the development of more disadvantaged regions of a country.

self-collected information on the location and opening date of industrial estates and SEZs in Indonesia, together with province-level panel data on the Gini coefficient to measure income inequality. First, we use standard panel data regression techniques to investigate the above relationship, where we also consider heterogeneities by broad geographical regions. This is then complemented with causal evidence from a synthetic control case study approach. Three zone openings are selected for the case studies. These are the opening of an industrial estate in 2008 in Banten, a relatively developed province on Java Island, and two other cases from two less developed, mostly rural provinces, Aceh and West Nusa Tenggara, opening their first industrial estate in 2014 and SEZs in 2017, respectively.

Indonesia is an interesting case to study the inequality consequences of economic zone policies. Since the 1970s, the country has opened about 120 industrial estates and - more recently - 11 SEZs. Economic zones in Indonesia may represent considerable locational advantages for businesses, as the country is known for its high transaction costs (Anas and Pangestu, 2020). Indonesian industrial policy also seems to work well in attacting foreign investors, Indonesia being the second-highest FDI recipient amongst ASEAN member states between 2015 and 2019.[4] Moreover, recent economic development has successfully pulled many Indonesians out of poverty (Miranti, 2010; Kis-Katos and Sparrow, 2015). Nevertheless, this process was also accompanied by growing income inequality. A recent World Bank report notes that the growth of the Gini coefficient in Indonesia was one of the highest among South-East Asian countries in the mid-2010s, raising concerns that the country is at risk of leaving its poor and most vulnerable behind (The World Bank, 2016). Although the Gini has declined in the most recent years, it remains at a relatively high level, especially in some parts of Indonesia such as the populous Java Island.[5]

Economic literature offers no clear guidance on how industrial place-based policies affect local income inequality, as the socio-economic impact of such policies depends on multiple interrelated factors (Duranton and Venables, 2019). Even if a policy explicitly targets a disadvantaged region with the aim to help poor locals, success may not be guaranteed (Neumark and Simpson, 2014). There are at least two channels through which industrial place-based policies can lead to an increase in local inequalities. One manifests itself through the in-migration of skilled workforce to the area where the policy takes place and the resulting gentrification of the neighborhood. The inflow of more affluent and skilled new residents

[4] Source: ASEAN Statistics Data Portal, Inward FDI Flows in million US$.

[5] Several factors have been identified as leading casuses behind the rise of income inequality in Indonesia. These are unequal access to education, high wealth concentration, low resilience, and regional differences in infrastructure provision (World Bank, 2016; Wicaksono et al., 2017).

can worsen the chances of less-skilled locals to benefit from the policy while it also raises the local cost of living (e.g. housing prices). This explanation is proposed by Reynolds and Rohlin (2015) to understand why the Empowerment Zone program in the U.S. (a place-based policy of tax incentives to create new jobs) increased income inequality in the affected regions. Another channel that could be responsible for economic zones having a detrimental impact on some local residents is related to land acquisitions. In agricultural communities, a land acquisition for industrial purposes reduces the land available for agriculture and may deprive some of the local farmers of their livelihood unless adequate compensation is provided. Although industrial development improves the lives of many through creating better infrastructure and employment, there may be groups of people left behind in this process. Economic zone development can as a result increase both poverty and inequality in its neighborhood - at least for a transitional period (e.g., Le et al., 2020, for Vietnam; Aggarwal and Kokko, 2021, for India).

Useful insights can be gained also from the international economics literature as to how industrialization and globalization-driven economic growth impact a country's income inequality. The classical Heckscher-Ohlin theory would predict that a country abundant in unskilled labor, like Indonesia, specializes in low-skilled production in the international division of labor. As a consequence, unskilled wages would rise relative to skilled wages, leading to a more compressed wage distribution, that is, declining income inequality. Curiously, this hypothesis does not find much support when contrasted with data. Empirical literature that links globalization and technological progress to income or wage inequality in developing countries tend to find that economic growth is in fact accompanied by growing inequality (e.g., Attanasio et al., 2004; Figini and Görg, 2011; Jaumotte et al., 2013; Gozgor and Ranjan, 2017; Dorn et al., 2018). A major explanation is that economic growth through technological progress is skill-biased, that is, it benefits those who possess higher skills (and capital) disproportionately. The tasks that are outsourced to developing countries within the international production chain may require relatively low skills. Nevertheless, these tasks are often still too complex for the unskilled labor force in these countries. The growing demand for skills raises the relative wages of skilled to unskilled workers (the so-called wage skill premium) and increases wage inequality (e.g., Feensta and Hanson, 1997; Autor et al., 1998).

Our study contributes to the literature that empirically assesses the role of economic zones in economic development. These papers typically address the question as to whether these zones are successful in attracting foreign investment, promoting exports, fostering productivity and creating more and better paying jobs. China's case with special economic zones is an especially well-documented success story (Schminke and Van Biesebroeck, 2013; Wang, 2013; Lu et al., 2019). Evidence on the experiences of other developing countries are more mixed, suggesting that success is dependent on the institutional context and other initial conditions (e.g., Aggarwal et al., 2008; Steenbergen and Javorcik, 2017; Alkon, 2018). In Indonesia, the importance of economic zones was studied by Winardi et al. (2019), who found that zones contribute to attract more investment, generate employment and enhance regional economic growth in their neighborhood. Firms located inside the zone are more productive than those outside, which is often attributed to the advantages offered by the zone such as low transportation costs and better infrastructure (Faradila and Kakinaka, 2020; Winardi et al., 2017). These benefitial effects however may not accrue in all circumstances (Aritenang and Chandramidi, 2020; Rothenberg et al., 2017).[6]

Research on economic zones in developing countries which also considers local distributional effects is especially scarce. There are two noteworthy exceptions. One is Picarelli (2016), who focuses on the local distributional impact of export processing zones in Nicaragua. Her findings, which are based on household expenditure data, reveal adverse distributional effects. The establishment of export processing zones in Nicaragua benefitted the already well-to-do households disproportinately more than households at the lower parts of the expenditure distribution. In contrast, Brussevich (2020) finds on Cambodian district-level data that SEZs reduced income inequality within the districts where they are located. This is because Cambodian SEZs boosted female employment and provided relatively well-paid jobs to an otherwise disadvantaged social group. She also finds however that SEZs increased the value of land more than wages in their district of location, suggesting that land owners may have benefited more than workers.

Our regression-based empirical findings suggest that, for Indonesia as a whole, a zone opening in a province is typically followed by a mild increase of income inequality in that province. This relationship is heterogenous geographically, suggesting that local conditions play a major role in mediating it. Similarly, the synthetic control case studies confirm that zone openings can contribute to rising inequality at least in the short run. In two of the three case studies we find growing income inequality in the first few years after the zone opening, but no evidence for an effect in the longer run. In the third case study (Mandalika SEZ in West Nusa Tenggara) we find no evidence for an effect on income inequality.

[6] Aritenang and Chandramidi (2020) have found no substantial evidence that SEZs in Batam city in Indonesia would enhance firm productivity. Rothenberg et al. (2017) study the Integrated Economic Development Zone (KAPET) program in the outer islands of Indonesia and find that the program failed to improve development outcomes in their districts of location.

These findings shed light on the importance of equity considerations when designing place-based policies. Namely, such policies can contribute to rising inequality even if they help reduce overall poverty. Our results show that such effects are present at least in the short run and call for development policies that are more socially inclusive. The concept of inclusive development may especially resonate in a country like Indonesia, with the political philosophy of *Pancasila* that emphasizes social justice to all Indonesian citizens (Gibson, 2017:11).

The paper is structured as follows. Section 2 discusses the history of industrial estates and SEZs in Indonesia. Section 3 presents recent trends of province-level income inequality and describes the database that we use in the subsequent empirical analysis. Regression-based evidence is presented in Section 4, while Section 5 is dedicated to setting out the synthetic control case studies. Finally, Section 6 concludes with a few policy recommendations.

2 Industrial estates and SEZs in Indonesia

Economic zones – our umbrella term for similar industrial place-based policies[7] – are geographically well defined areas that are designated for industrial purposes to promote economic development in a region. For investors and businesses to move into such areas, policymakers offer fiscal and non-fiscal incentives. These may include lower taxes, a more business-friendly regulatory environment or better physical infrastructure than that available outside the economic zone (e.g., Lin, 2017). The provision of economic zones can be viewed from the New Structural Economics (NSE) perspective proposed by Lin (2011) of the World Bank, which emphasizes the role of the government in facilitating economic growth by the provision of quality infrastructure and institutions.

Indonesia's policy of economic zones dates back to the beginning of the 1970s, when the country started to set up its first industrial estates (*Kawasan Industri*) as a form of infrastructure that supports industrial activities.[8] According to the official definition, an industrial estate is an estate wherein industrial activities are centralized, complete with supporting facilities and infrastructure developed and managed by an Industrial Estate Company."[9] It

[7] Over time, different names have been attached to more or less the same concept (industrial estates, free trade zones, export processing zones, special economic zones, etc.), reflecting the objectives and functions these establishments are meant to serve in different countries and times.

[8] The legal and institutional framework governing economic zone policy in Indonesia is discussed in detail in Aggarwal (2022).

[9] Regulation of Government of The Republic of Indonesia Number 142 of 2015 on Industrial Estate, (unofficial English translation).

serves the objectives i. to accelerate the spread and even distribution of industrial development, ii. to improve industrial development efforts with an environment-based perspective, iii. to enhance investment and industrial competitiveness, and iv. to provide location certainty following the spatial plan. The country's first industrial estate was set up in 1970 in the capital city Jakarta with the name Jakarta Industrial Estate Pulo Gadung (Octavia, 2016), followed by others located in different parts of Indonesia, such as in Surabaya and Cilacap (in 1974), Medan (1975), Cirebon (1984), and Lampung (1986) (Kwanda, 2000). Nevertheless, the growth remained limited until the late 1980s, when a series of regulatory reforms were initiated and the industrial estate business was opened to the private sector (Aggarwal, 2022). Afterwards, industrial estates have proliferated in Indonesia. Our list of operating economic zones as of end-2020 includes 118 industrial estates.

More recently, industrial place-based policies have gained new momentum in Indonesia. Since 2014, President Joko Widodo has directed the government's priority to accelerate the new establishments of special economic zones (*Kawasan Ekonomi Khusus, KEK*), supported by a SEZ act (Octavia, 2016). SEZs refer to "zones with certain boundaries within the territories of the unitary state of the Republic of Indonesia, and designated to carry out the economic function and are granted certain facilities and incentives."[10] As opposed to industrial estates, SEZs are established in a wider array of economic sectors and may be dedicated to various purposes (e.g., export processing, logistics, manufacturing, technology development, or tourism). The stated objectives of the SEZ policy are to attract foreign investment, enhance economic productivity and reduce inequality between the provinces of Indonesia. To better achieve these goals, investors in SEZs are offered somewhat more favorable direct tax incentives than what is generally applied in the country[11] and Indonesia's relatively restrictive rules on FDI inflows and foreign equity holdings have also been relaxed for SEZ investors.[12] At the beginning of 2021, the number of approved SEZs was 15, of which 11 were operating and 4 were under construction.[13] The Indonesian government also

[10] Regulation of the Government of The Republic of Indonesia Number 39 of 2009 on Special Economic Zone, (unofficial English translation).

[11] Indonesia offers massive direct and indirect tax incentives for new investments in 18 targetted industries. Most tax incentives are therefore industry-based and not place-based (Aggarwal, 2022).

[12] For foreign investors in SEZs, Indonesia's negative FDI list does not apply, and foreign equity holdings of up to 100% are permitted. However, land ownership by foreigners remains prohibited even within SEZs (Aggarwal, 2022).

[13] Source of information: Dewan Nasional Kawasan Ekonomi Khusus Republic Indonesia (Republic of Indonesia National Council for Special Economic Zone), `https://kek.go.id/peta-sebaran-kek`, last update on 11 February 2021).

has the intention to transform some of the industrial estates into SEZs, with the purpose to improve their efficiency.

Importantly, neither industrial estates nor SEZs aim to reduce local inequalities. Although the SEZ policy mentions the need to reduce inequalities between provinces, it does not address distributional issues between residents within provinces. Of course, we cannot rule out the possibility that differences between industrial estates and SEZs in terms of their policy objectives and scope of activities may lead to differences in terms of impact on inequality. However, we have no a priori expectations as to the direction of these possible differences. Given these considerations as well as the small number of SEZs in operation, we have decided not to distinguish between the two forms of economic zones in the first part of our empirical analysis. In the second part, the synthetic control case studies will discuss the cases of two industrial estates and one SEZ.

For the purposes of this project we have set up a list of industrial estates and SEZs in Indonesia that includes their names, exact locations and the years when they started to operate.[14,15] This information was acquired from the Ministry of Industry Indonesia and the Republic of Indonesia National Council for Special Economic Zone.

The number of economic zones in Indonesia rose dynamically over time. Table 1 shows the number of operating zones by year and main island. From a total of 9 zones in 1990 the number rose to 129 by 2020. Zone establishments proliferated especially in the most recent decade – almost half of the existing economic zones opened between 2010 and 2020. At the same time, the distribution of zones over space remained rather unequal, both between main islands as well as within-island between-province. Most of the zones are located on the islands of Sumatra and Java, as also shown in Figure A1, a map of Indonesia with geocoded locations of all operational zones. The champion province is West Java on Java island with 35

[14]We consider the operation start as the 'birth' of the economic zone, even though a zone may have some impact on its neighborhood before that date due to anticipatory effects or boosting construction activities. However, we believe that, when focusing on the impact on inequality, it is more appropriate to focus on the date of operation start because the impact on inequality is likely to unfold only when the effects reach the wider population.

[15]It should be noted that our study does not consider the full range of economic zones in Indonesia, which is comprehensively described in Aggarwal (2022). In particular, we do not consider bonded zones separately from industrial estates. Indonesia's bonded zones are traditional forms of export processing zones and, with some exceptions, must be located within industrial estates. Further, we do not include the thirteen Integrated Economic Development Zones (KAPETs) in the current study. The KAPET program, which was launched in the second half of the 1990s to promote the development of lagging regions in eastern Indonesia, is considered largely unsuccessful in having an impact and was beset with several implementation problems (Rothenberg et al., 2017; Rothenberg and Temenggung, 2019).

Table 1: Economic zones by main islands of Indonesia

Island	Population million	GDRP IRD trillion	Number of zones 1990	2000	2010	2020
Sumatra	58.60	3,427	3	16	26	40
Java	151.00	9,487	4	30	39	71
Kalimantan	16.50	1,294	1	1	1	9
Sulawesi	19.70	1,018	1	1	1	5
Outer islands	22.30	852	0	0	0	4
Total	268.10	16,078	9	48	67	129

Note: Authors' calculations. Population and GDRP (Gross Domestic Regional Product) figures refer to year 2019 and are sourced from Statistics Indonesia. GDRP is based on expenditure and expressed in current market prices. The number of zones do not include zones under construction. We follow Kis-Katos and Sparrow (2015) in defining the five main islands. Provinces in *Sumatra*: Bengkulu, Jambi, Kep. Bangka-Belitung, Kep. Riau, Lampung, Aceh, Riau, West Sumatra, South Sumatra, North Sumatra; *Java*: Banten, DI Yogyakarta, DKI Jakarta, West Java, Central Java, East Java; *Kalimantan*: West Kalimantan, South Kalimantan, Central Kalimantan, East Kalimantan, North Kalimantan; *Sulawesi*: Gorontalo, West Sulawesi, South Sulawesi, Central Sulawesi Southeast Sulawesi, North Sulawesi; *Outer islands*: Bali, North Maluku, Maluku, West Nusa Tenggara, East Nusa Tenggara, West Papua, Papua.

economic zones, followed by the Riau Islands with 26 zones (Sumatra), Banten with 14 zones and East Java with 11 zones (both on Java). Out of the remaining Indonesian provinces, 18 have single-digit economic zones and 12 have no operating zones.

This concentration of zones largely mirrors the uneven geographical distribution of population and economic activity within Indonesia. Namely, Java and Sumatra are historically the most populous regions with the highest GDP (Table 1). It is no surprise that economic zones are not located randomly, but the choice of location depends on agglomeration forces (e.g., the availability of skilled workers and infrastructure) as well as on political objectives. The targetted establishment of economic zones in more remote and less developed regions has been declared a priority in Indonesia only more recently. Examples of zones, whose recent establishment was also driven by the aim of reducing regional inequalities, are the Mandalika SEZ in West Nusa Tenggara (one of our Synthetic Control case studies) which operates since 2017, the Morotai SEZ in North Maluku, the Sorong SEZ in West Papua, or the Bitung SEZ in North Sulawesi (all three operating since 2019).

3 Data and trends of income inequality

This study uses secondary data on the provincial level at the annual frequency. We construct an unbalanced panel database with several economic indicators for the 34 provinces of Indonesia and for years between 2001 and 2020. In the estimation sample the number of provinces reduces to 31 because important variables are missing for two provinces (West Papua, West Sulawesi), while a further province (North Kalimantan) was created only in 2013. Data are collected from three major sources: Statistics Indonesia[16], the Ministry of Investment Indonesia (formerly known as Investment Coordination Board)[17], and the World Bank's Indonesia Database for Policy and Economic Research (INDO-DAPOER).

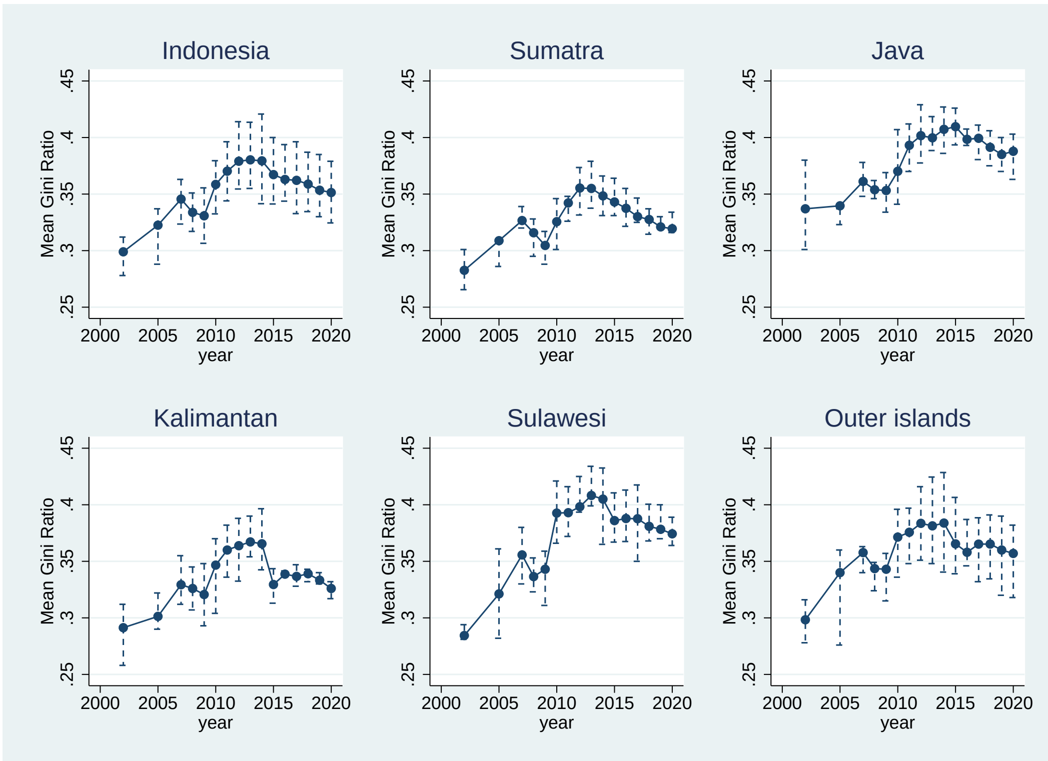
The Gini coefficient is sourced from Statistics Indonesia, which calculates the Gini based on consumption expenditure information from the National Socio-Economic Survey (Susenas). The Gini is available for 2002, 2005 and every year from 2007 onward. It is assessed once a year up until 2010 and twice a year (in March and September) starting from 2011. For these more recent years we take the simple average of the two observations to form an annual Gini. The other basic indicators include population, the Gross Domestic Regional Product (GDRP), GDRP per capita, government expenditures in GDRP, FDI inflows, employment statistics such as unemployment, underemployment and sectoral employment shares, popu-

[16]Badan Pusat Statistik Indonesia (`https://www.bps.go.id/`)

[17]Badan Koordinasi Penanaman Modal

lation density, the level of the minimum wage, the poverty rate, the literacy rate and the net enrollment rate to secondary education. These indicators are mainly used as control variables in the panel regressions as well as predictors of future income inequality in the Synthetic Control case studies.

Figure 1: Trends of income inequality for Indonesia and its main islands



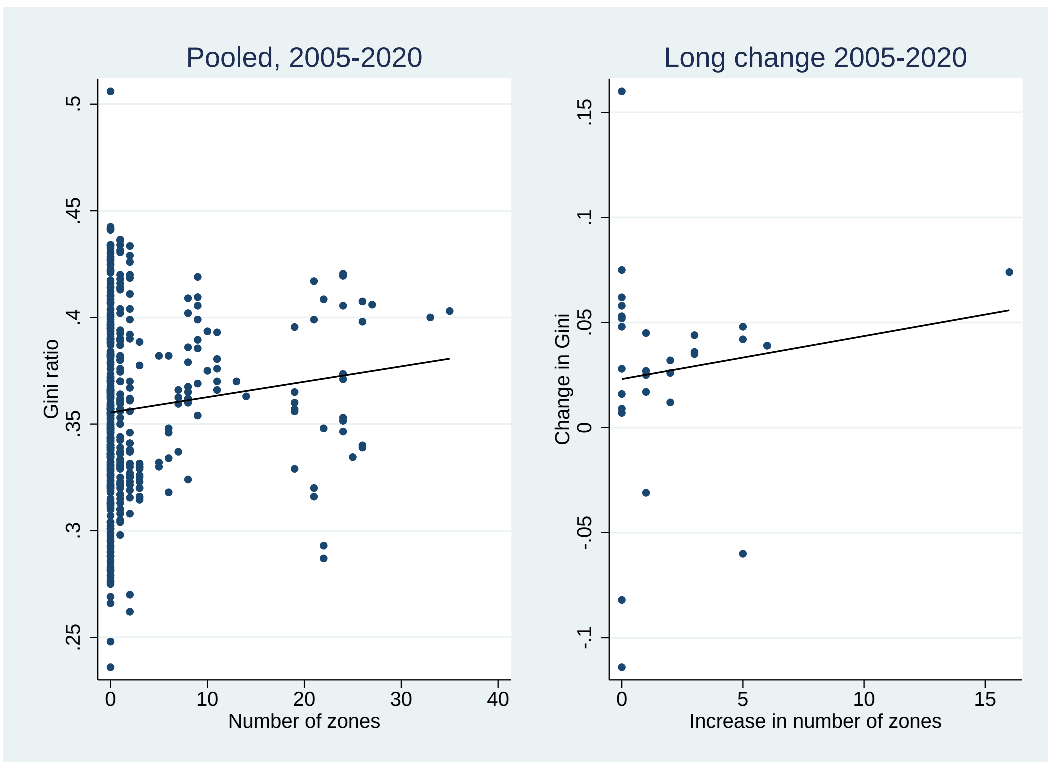
Note: Means and interquartile ranges of province-level Gini coefficients plotted by year. Before 2007, the Gini is available only for 2002 and 2005. Own calculations based on the Gini coefficients published by Statistics Indonesia. North Kalimantan and East Kalimantan are excluded due to their separation in 2013.

Income inequality in Indonesia showed an upward trend until the middle of the last decade, as presented on the upper-left chart in Figure 1. Although the trend has been declining since then, the level of inequality remained significantly higher than at the start of our sample period. This hump-shaped trend was characteristic to all major regions of Indonesia. Nevertheless, country averages hide significant regional variations in the level of inequality, as suggested by the interquartile ranges displayed on the charts. The group of provinces with Gini ratios above the country average is dominated by provinces on Java and Sulawesi. Especially some provinces on Java – DI Yogyakarta (Gini of 0.43), West Java

(0.40), and DKI Jakarta (0.39) – recorded top levels of inequality in 2020. In general, the Gini is typically higher in the more urbanized areas of Indonesia.

Clearly, there are multiple factors that may influence the level of income inequality within a region. This study aims to find out whether the presence of economic zones belong to them. In a next step, we plot inequality against the number of economic zones, without conditioning on any other factor that may confound this relationship. Figure 2 suggests that, if anything, the correlation is slightly positive. Provinces in years with more zones tend to display higher inequality levels (left chart). And the same applies to growth rates between 2005 and 2020 (right chart). On average, income inequality rose more in provinces which set up a higher number of economic zones during this 15-year-long period.

Figure 2: Correlation of number of zones with income inequality



Note: Left: Scatter plot on the pooled sample of provinces for all years between 2005 and 2020. Right: Scatter plot of changes from 2005 to 2020. Both graphs exclude North Kalimantan and East Kalimantan due to their separation in 2013.

4 Regression-based evidence

The primary aim of this paper is to estimate how the establishment of economic zones in some provinces of Indonesia affected income inequality within those province. The slight positive correlations presented in Figure 2 are by no means evidence of a causal relationship of economic zones raising inequality. There may be factors which can contribute to rising inequality and at the same time correlate positively with economic zone location (omitted variable bias). Also, a positive correlation can arise if a government deliberately establishes economic zones in provinces where inequality is higher than elsewhere (selection bias). This section aims to eliminate some of these biases by employing fixed-effects panel estimation. The estimation with province fixed effects helps us to control for all forms of time-invariant heterogeneity at the province level that can lead to estimation bias and therefore provides more reliable estimates than pure cross-sectional or pooled estimates (Gujarati and Porter, 2009).

The regression equation with province fixed effects α_i takes the following form:

$$Gini_{it} = \beta Zone_{it} + X_{it}'\gamma + X_{i,0}'\delta_t + \alpha_i + u_{it}. \quad (1)$$

The dependent variable $Gini_{it}$ is the Gini coefficient in province i and year t. Its value ranges from zero to one, with a value closer to 1 meaning that the province has a more unequal income distribution. The parameter of interest is β which quantifies the relationship between the Gini and the number of zones variable, $Zone_{it}$. Because the fixed-effects estimator exploits the time variation of our province panel, β is identified from the zone openings that occurred during our sample period, of which there were 44 (27 on Java and 17 in other parts of Indonesia). Time-varying control variables are collected in the vector X_{it}'. We also allow for time-invariant "base" variables to influence the inequality trends of the provinces (similar to, e.g., Lu et al, 2019). These base variables represent initial conditions in the provinces, which are then interacted with year dummies ($X_{i,0}'\delta_t$). The first element of $X_{i,0}'$ is always the unit vector, i.e., all specifications include at least a common time trend. The common time trend accounts for macroeconomic shocks that were common to all Indonesian provinces in any given year. The idiosyncratic error term is denoted by u_{it}.

We start with the simplest specification with no control variables and sequentially enrich the model. In doing so, one aim is to shut down channels that may be further sources of estimation bias. One source of bias may be related to differences between provinces in their initial conditions. Although in most cases province fixed effects eliminate biases that could arise from time-invariant province heterogeneity, this rests on the assumption that the province heterogeneity has the same effect on the dependent variable in each time

Table 2: Panel estimates with heterogeneous trends

Depvar: Gini ratio	(1)	(2)	(3)	(4)
Number of zones	0.00311**	0.00300**	0.00304**	0.00236*
	(0.00115)	(0.00118)	(0.00129)	(0.00129)
GDRP (log)	0.0331	0.0296	0.0331	0.0279
	(0.0249)	(0.0234)	(0.0211)	(0.0245)
Province FEs	✓	✓	✓	✓
Year effects	✓	✓	✓	✓
Year × Base GDRP p.c.		✓		
Year × Base Enrollment			✓	
Year × Base Agri. share				✓
Within R-squared	0.539	0.588	0.576	0.572
Observations	429	429	429	429
F-test for joint significance of interacted year effects				
F(13, 30)		11.34	8.04	16.53
Prob>F		0.0000	0.0000	0.0000

Note: Fixed-effects estimation of equation (1) on an unbalanced panel of 31 provinces over 14 years (2002, 2005, 2007-2018). All regressions include a dummy variable which is 1 for East Kalimantan from 2013 onward to control for its separation from North Kalimantan. Standard errors (in parentheses) are clustered by province.

period (Wooldridge, 2010, Ch. 10). Initial conditions however may influence the future dynamics of inequality, having different effects in different years. To address this concern we include province-specific time trends that depend on initial conditions. We consider three base variables to represent such initial conditions: i. the level of economic development as captured by the log GDRP per capita, ii. the skill level of the workforce (secondary school enrollment ratio), and iii. the initial structure of the economy, which we proxy with the share of employment in agriculture. We take the simple average of the annual values of these variables (when nonmissing) over the period 2001-2005 as initial values.[18] Note that the three base variables capture different aspects of the long-term development processes –

[18]The results are robust to taking the 2001 values only and excluding the provinces where the 2001 value is missing from the estimation sample.

economic growth, human capital formation, structural transformation.

Table 3: Panel estimates with time-varying controls

Depvar: Gini ratio	(1)	(2)	(3)	(4)
Number of zones	0.00300**	0.00228**	0.00227*	0.00153
	(0.00118)	(0.00111)	(0.00113)	(0.00145)
GDRP (log)	0.0296	0.0148	0.0186	0.00248
	(0.0234)	(0.0174)	(0.0176)	(0.0222)
Unemployment rate		-0.443**	-0.434**	-0.434**
		(0.185)	(0.188)	(0.177)
Underemployment rate		-0.0605	-0.0612	-0.0502
		(0.0498)	(0.0503)	(0.0461)
Poverty rate			-0.000876	-0.00119
			(0.00167)	(0.00138)
Population density (log)			-0.0236	-0.0161
			(0.0221)	(0.0257)
FDI stock per capita				-0.00034
				(0.0004)
Gov.exp share in GDRP				-0.203
				(0.163)
Province FEs	✓	✓	✓	✓
Year effects	✓	✓	✓	✓
Year $\times$ Base GDRP p.c.	✓	✓	✓	✓
Within R-squared	0.588	0.611	0.613	0.623
Observations	429	429	429	429

Note: Fixed-effects estimation of equation (1) on an unbalanced panel of 31 provinces over 14 years (2002, 2005, 2007-2018). All regressions include a dummy variable which is 1 for East Kalimantan from 2013 onward to control for its separation from North Kalimantan. Standard errors (in parentheses) are clustered by province.

Further estimation biases may arise from the presence of time-varying confounders, which can be observed or unobserved to us. To mitigate this source of bias we control for a set of observed time-varying province characteristics in the regression. We include in all regressions the GDRP value to control for the economic size of the provinces. In further specifications, we also include the unemployment and underemployment rates to account for local labor market conditions, the poverty rate and the population density, which are meant to capture the presence of people with, respectively, very low and very high incomes. High population density signals big cities and their metro areas where the highly skilled workforce is concentrated. We also account for the importance of foreign investors in the province (measured by the per-capita cumulated FDI inflows) and the degree of fiscal redistribution (proxied by the share of government expenditures in GDRP). When interpreting the estimation results, it will be important to bear in mind that including some of the time-varying variables can potentially lead to overadjustment. This can occur when the variable in question represents an important channel through which economic zones affect inequality, which is then eliminated. Labor market variables, population density, or foreign presence, e.g., could potentially represent such channels. Also, the degree of fiscal redistribution may be endogeneous to inequality developments (e.g., Gozgor and Ranjan, 2017). Therefore, estimates from regressions with time-varying control variables must be interpreted with these caveats in mind.

The estimation results are reported in Table 2 and Table 3, with subsequently broader sets of control variables. Overall, we find support for the hypothesis that, for the average province in Indonesia, the establishment of economic zones led to higher within-province income inequality during the period under consideration. The estimate is small, however, indicating an increase in the Gini of 0.003 Gini points associated with one zone opening, which corresponds to an 0.8% increase in the sample average Gini. This estimate is remarkably robust to the inclusion of heterogeneous year effects with respect to the level of base variables (columns (2)-(4) in Table 2). The Year $\times$ Base variable interactions are jointly significant in all regressions and their coefficients have reasonable signs. Provinces display a lower Gini path if they are initially more developed and skilled, while they have a higher Gini path if their economy is initially more agricultural (see Figure A2 in the Appendix). As we gradually include more time-varying controls in the regressions, the estimate tends to decrease but it remains statistically significant in all but the last regression of Table 3, which includes all control variables jointly. Of these additional control variables, only the unemployment rate turns out to be a significant predictor of the Gini; the Gini increases when unemployment decreases. A situation in which employment creation coexists with rising inequality can be explained by skill-biased growth and a rising skill wage premium due to the scarcity of skills. Foreign direct investment does not seem to affect income inequality, which is consistent with previous findings on Indonesia (Fazaalloh, 2019).

As a final step in our regression-based analysis, we briefly investigate if there are regional heterogeneities in the estimated effect. Because zone openings are much concentrated on the Java island, we choose to differentiate between two regions: Java and the rest of the provinces. Our modified regression equation therefore estimates two βs for the two regions, where the regions are indicated by the province-specific dummy variables $Java$ and $Rest$.

$$Gini_{it} = \beta^{Java} Zone_{it} \times Java_i + \beta^{Rest} Zone_{it} \times Rest_i + X'_{it}\gamma + X'_{i,0}\delta_t + \alpha_i + u_{it}. \quad (2)$$

The corresponding estimation results are presented in Table A1 for specifications identical in terms of included control variables to columns (1) and (2) of Table 2 and column (4) of Table 3. The results reveal that the positive association we find between the establishment of new economic zones and income inequality is mainly driven by zone openings on the Java island. For the average zone opening outside Java the estimate is statistically zero. This 'Java differential' does not get eliminated by the inclusion of control variables, though it is reduced. This shows that there is considerable regional heterogeneity in the relationship between zone openings and local income inequality, a likely explanation of which is that local circumstances, both observed and unobserved, can play a major role in mediating this relationship.

5 Case study analysis

The previous section revealed a small positive correlation between the opening of economic zones and income inequality in some – but not all – parts of Indonesia. Motivated by this fact and the limits of a province-level regression analysis, this section turns to a different and more novel econometric approach. We aim to investigate further the potential of a causal relationship with the use of a comparative case study approach, the synthetic control method (SCM), which we apply to three recent events of economic zone openings in Indonesia.

5.1 The Synthetic Control Method

The SCM is a relatively novel statistical method that was developed for comparative case studies. It is used in settings when some units - mostly geographical - are affected by an event or policy, while other similar units are not. Developments in the affected units can then be compared to developments in the unaffected units to infer the effects of the policy or event. A major practical advantage of the method is that it only requires aggregate data, which is often more readily availabe than micro-level data.

The SCM was pioneered by Abadie and Gardeazabal (2003) and was developed further and extended with techniques for statistical inference by Abadie, Diamond and Hainmueller

(2010; 2015). Since its inception it has been featured in numerous empirical applications. It aims to examine the causal impact of policies or events that take place at an *aggregate* level, e.g. a policy enacted across an entire state or province. As a prime example, Abadie, Diamond and Hainmueller (2010) measure the effectiveness of a tobacco control program introduced by the US State of California in 1989, and use other US states as comparison units.

This section applies the SCM on three selected cases of recent economic zone openings in three different provinces of Indonesia: one industrial estate opened in Banten in 2008, another opened in Aceh in 2014, and an SEZ designated to tourism opened in West Nusa Tenggara in 2017. We assume that the zone openings (*treatments*) are policies that take place on the level of the province, and then compare, in each of the three cases, the post-opening evolution of income inequality between the province where the economic zone was set up (*treated* province) and a combination of other - arguably unaffected - provinces (*synthetic control*).[19]

In what follows we present the estimation strategy behind the SCM, adapted to the current application. The description is intentionally kept simple; for a more general exposition see, e.g., Abadie, Diamond and Hainmueller (2010). Let us take the treated province as the first province indexed by 1 and denote the year in which the economic zone was opened by T_o. Our aim is to measure the change in the Gini coefficient of the treated province in the post-treatment years, $t \geq T_o$, that can be attributed to the zone opening. This treatment effect for year t, denoted by β_{1t}, is

$$\beta_{1t} = Gini_{1t} - Gini_{1t}^{N}, \tag{3}$$

that is, the difference between the actual value of the Gini coefficient for the treated province in year t ($Gini_{1t}$), and the counterfactual Gini ($Gini_{1t}^{N}$), that would have been the level of income inequality in the treated province in year t had the economic zone not been opened.

Clearly, the counterfactual Gini is not observed. The SCM overcomes this problem by approximating the counterfactual with the synthetic control, where the synthetic control is created from available comparison provinces. How this is done lies at the heart of the

[19]It needs to be acknowledged that our approach deviates from the classical application of the SCM in that the establishment of an economic zone is not an aggregate policy per se. Economic zones belong to place-based policies with geographically localized effects, and one cannot know in advance how far these effects extend in space. Therefore, this analysis relies on the assumptions that i. the effects of an economic zone are contained within the province where the zone is located (as well as in the immediate neighboring provinces if the zone is located close to a province border), and that ii. the effects are large enough to show up in the province-level statistics.

methodology behind the SCM. Intuitively, the synthetic control is the linear combination of comparison provinces that best approximates the characteristics of the treated province before the opening of the economic zone. More formally, the synthetic Gini in year t ($Gini_{SC,t}$) is a linear combination of the Ginis of R potential comparison provinces (also called the control pool) in year t with weights w_r^*.

$$Gini_{SC,t} = \sum_{r=1}^{R} w_r^* Gini_{rt}. \tag{4}$$

The weights are restricted to sum to one and to fall between 0 and 1, and they are chosen such that the synthetic control most closely resembles the treated province in the pre-treatment years both in terms of income inequality as well as in terms of other characteristics that may predict inequality. More formally, for the optimally set weights w_r^* it must be approximately true that

$$\sum_{r=1}^{R} w_r^* Gini_{rt} = Gini_{1t} \quad \text{for every } \; t < T_o \tag{5}$$

and

$$\sum_{r=1}^{R} w_r^* \mathbf{Z}_r = \mathbf{Z}_1 \quad \text{for the average of the pre-treatment years.} \tag{6}$$

The matrix $\mathbf{Z}$ contains variables that are supposed to influence the future development of inequality in a province but they themselves are not affected by the treatment. The typical SCM application takes the average values of these variables over the entire pre-treatment period but researchers can deviate from this practice by taking averages over subsets of this period only.

Once the optimal SC weights are found and the Gini of the synthetic control is calculated, the SCM estimate for the treatment effect is simply obtained as the difference in Gini in the post-treatment years between the treated province and the synthetic control

$$\hat{\beta}_{1t} = Gini_{1t} - Gini_{SC,t}. \tag{7}$$

One of the advantages of the SCM over traditional regression methods lies in the way the SC weights are determined. Since the weights are all restricted to be greater or equal to zero, the method minimizes the possibility of an extrapolation bias (Abadie, Diamond and Hainmueller, 2015). A further attractive feature of the SCM is its transparency, as the weights make it explicit how individual control units contribute to the counterfactual. A disadvantage though is that the SCM is more susceptible to interpolation biases relative to more traditional estimation methods.

5.2 Three case studies

Recall that economic zones in Indonesia are highly concentrated geographically (Table 1). Provinces on Java and Sumatra had several industrial estates already back in the 1990s. And most new zones that appeared during the sample period of this study have been opened in the very same provinces. The rest of the provinces typically started to establish economic zones only in the most recent years. These features drive (and limit) the choice of cases for our comparative case studies.

An SCM case study needs to have sufficiently long pre-treatment and post-treatment periods. This means that, to be able to isolate the effect of one opening event, we need zone openings which were neither preceded nor followed by other zone openings in a reasonably wide time window. Provinces that frequently open zones or provinces that opened their first zone only in the most recent years therefore do not qualify as valid case study candidates. These considerations limit the number of potential candidates to five. Out of the five, only three cases produced at least a reasonably well-performing synthetic control, so we ended up with three case studies. Fortunately, these three cases represent the diversity of Indonesian provinces relatively well. They include the opening of an industrial estate in Banten, a relatively developed province on Java Island, and two other cases from two less developed, mostly rural provinces, Aceh and West Nusa Tenggara, opening their first industrial estate and SEZ, respectively. The location of the three zones are shown on Figure A3 as large green dots.

Taman Tekno BSD Industrial Estate in Banten (2008). Banten province on the Java Island opened the Taman Tekno BSD industrial estate as its ninth industrial estate in 2008. It is a multipurpose estate that, in addition to industrial purposes, also serves as a residential and commercial hub. It is located close to the province borders with two other provinces, West Java and the capital city of Jakarta. We find this case especially interesting because it represents one of the economic zones on the Java Island. While being the most developed region of Indonesia, Java is also characterized by the highest level of income inequality. During the period 2005-2014 no other economic zones were opened in Banten. This leaves us with a relatively short pre-treatment period (3 years, 2005-2007) and a comparatively long post-treatment period (7 years, 2008-2014). Unfortunately, the shortness of the pre-treatment period can have negative consequences for the goodness of fit the SCM can achieve, which one needs to keep in mind when interpreting the results.

Perikanan Lampulo Industrial Estate in Aceh (2014). The province of Aceh lies on the westernmost part of the Sumatra Island. It is a predominantly agricultural province in Indonesia, which is also relatively rich in natural oil and gas. The first industrial estate of Aceh, the Perikanan Lampulo Industrial Estate, was opened in 2014 at the fisheries port next to the province's capital city Banda Aceh and far from other parts of Sumatra. The activities of the industrial estate are primarily centred around the fisheries industry. No further zones were opened in Aceh until 2018, which provides us with a 4-year long post-treatment period (2014-2018). Since it is the first zone of the province, the pre-treatment period is comfortably long. Nevertheless, we decide to shorten it to 7 years (2007-2013) mainly because Aceh suffered a devastating earthquake and tsunami in December 2004 (Sumatra–Andaman earthquake) with severe socio-economic consequences for the next few years, which we chose to exclude from our sample.

Mandalika Special Economic Zone in West Nusa Tenggara (2017) Our third case study is a SEZ designated for tourism, the Mandalika SEZ, which came into operation in 2017 in West Nusa Tenggara. The province of West Nusa Tenggara comprises of the western portion of the Lesser Sunda Islands and lies between the provinces of Bali and East Nusa Tenggara. (In our classification it belongs to the group of "Outer islands".) West Nusa Tenggara is considered to be one of the least developed provinces of Indonesia, with most of its population still living from agriculture. In recent years, tourism has becoming a rising sector in the region. Beside obvious economic advantages, the expansion of tourism can also pose a threat to the agricultural communities, as touristic complexes sometimes require the acquisition of land previously used by farmers.[20] This is a prime reason why we consider this case interesting to study from an inequality point of view. The Mandalika SEZ was the first economic zone opened in West Nusa Tenggara and remains the only one to date. We start the pre-treatment period from 2010 because starting it from earlier results in a too small donor pool. As a result, the pre-treatment period is 7-years (2010-2016) and the post-treatment period is 4-years long (2017-2020).

5.3 Selecting control pools and predictors

As a next step, one needs to determine the donor pools and the predictor sets for each of the three case studies. Several assumptions have to be met about the nature of the donor pool

[20]Hasudungan et al. (2021) conclude that there is a negative relationship between the expansion of the agricultural and tourism sectors in Indonesia. This trade-off could be due to the fact that the two sectors compete for land, a scarce production input that both sectors use intensively.

and the predictor variables for the SCM to accurately estimate a policy's effect (McClelland and Gault, 2017). Listed below are three crucial assumption that motivate our selection.

1. No province in the control pool can have a similar zone opening.
2. The zone opening in the treated province cannot affect the Gini coefficient in the provinces of the control pool.
3. The values of the predictor variables for the treated province cannot be outside any linear combination of the values for the provinces in the control pool.

In line with assumption 1, we make sure that only those provinces get into the donor pool which do not have a zone opening during the case study sample period. Recall that the sample periods are 2005-2014 for Banten, 2007-2017 for Aceh, and 2010-2020 for West Nusa Tenggara. Also, we exclude West Java and DKI Jakarta from the donor pool of the Banten case study because the industrial estate in question is only a few kilometers away from the border between Banten and these two provinces, and therefore they are considered too close to meet Assumption 2. Finally, we exclude North Kalimantan and East Kalimantan from all the three donor pools because these provinces split in 2013.

Next, we consider a large set of potential predictor variables and check whether assumption 3 holds over the respective pre-treatment sample years. The list of potential predictors include the following province-level variables: pre-treatment values of the Gini coefficient, log GDRP value, log GDRP per capita, poverty gap, literacy rate, net enrollment rate to secondary education, population density, government expenditure as share of GDRP, share of agricultural employment in total employment, log minimum wage, cumulated FDI inflows per capita, as well as the unemployment and underemployment rates. We follow the literature and average the predictor variables, with the exception of the lagged Ginis, over the entire pre-treatment period.[21,22] As for lagged Ginis, we take the Gini of the immediate pre-treatment year (2007 for Banten, 2013 for Aceh, and 2016 for West Nusa Tenggara) and a few more - but not all - pre-treatment years. Kaul et al. (2018) argue that including all outcome lags as separate predictors renders all other predictors irrelevant and threatens the estimator's unbiasedness.

As a result of this selection process, we end up with donor pools of 22 provinces for Banten, 21 provinces for Aceh and 14 provinces for West Nusa Tenggara (Table A2) and three lists of potential predictors specific to the three case studies.

[21] See Jordan et al. (2021).

[22] One could argue that every zone opening is preceded by a construction phase, during which some of our economic indicators - particularly FDI inflows - may already be affected. To account for this possibility, we double-check our results by modifying the pre-treatment period for the FDI variable to end two years before the treatment year. The main results are robust to this change.

5.4 Results

Having determined the donor pool and the list of predictor variables, the next step is to run the SCM procedure to create the synthetic control via choosing the optimal SC weights.[23] To find the model that produces the smallest prediction error (Root Mean Squared Prediction Error, RMSPE), we try several combinations of the variables in the predictor set (considering all combinations that include at least 5 predictors other than the lagged Ginis) and choose the model with the smallest RMSPE.

The resulting SC weights are presented for each case study in Table A2. The synthetic Banten is a linear combination of five provinces, Lampung and South Kalimantan with 43% and 31% weights, respectively, and Riau, Papua and Bali with single-digit weights. Synthetic Aceh is 60% Bangka-Belitund Island, 26% Central Kalimantan and single-digit percentages of South Sulawesi, South Sumatra and Jambi. Synthetic West Nusa Tenggara is a composition of three provinces, East Nusa Tenggara, Southeast Sulawesi and West Sulawesi, with roughly equal weights.

Let us evaluate the results separately for each case study.

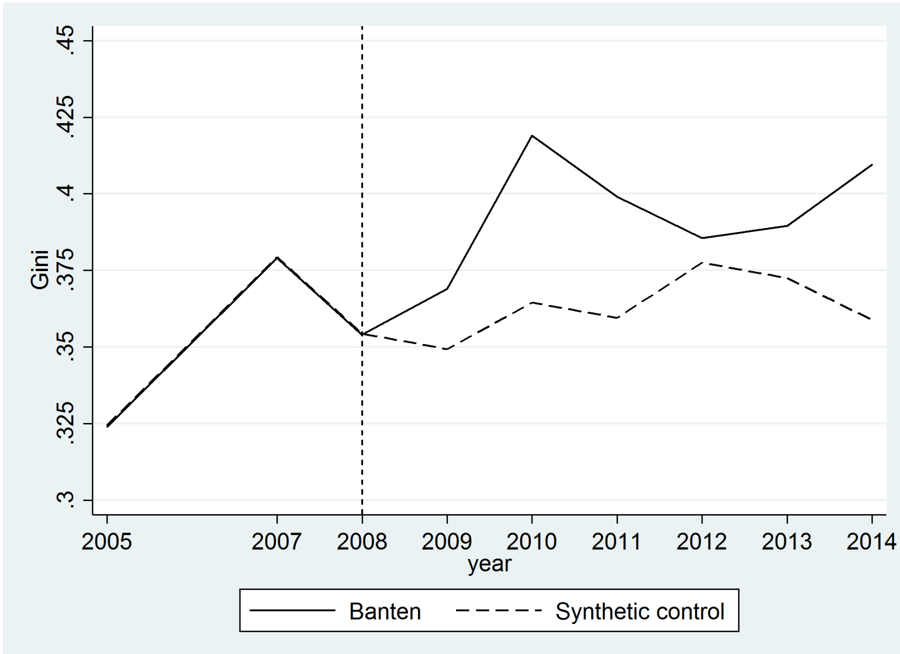
5.4.1 Banten 2008

Figure 3 displays the path of the Gini coefficients for Banten and its synthetic control in the pre- and post-treatment years. The two lines are very close before the 2008 treatment year. In the first two years after treatment, the true Gini increases by about 0.05 Gini points and, although it declines later, remains above the synthetic Gini throughout the entire post-treatment period.

When evaluating this result the question arises as to how well the synthetic Banten represents what the situation would have been in Banten in the absence of the treatment. We can examine how closely the synthetic Banten approximates the true Banten in the pre-treatment period. The pre-treatment Ginis are almost identical but this can be misleading given the shortness of the pre-treatment period in this case study (also, the Gini is not available for year 2006). In addition, we can check the goodness of fit in terms of all the predictors in the model. The three columns of Table A3 present the pre-treatment values of the predictors for the true Banten, the synthetic Banten, and the population-weighted average of the donor pool provinces. We can conclude that the SCM is effective in the

[23] We use STATA's synth function and set the nested optimization option for better performance at the expense of longer computing time.

Figure 3: Inequality - Banten vs Synthetic Control



sense that the synthetic Banten is closer to the true Banten than the average of the donors considering all the predictors.

Nevertheless, the approximation is not perfect. Synthetic Banten differs from the true Banten in that it has a smaller economic size, higher poverty, and lower literacy. This is not surprising since Banten is one of the more developed provinces in Indonesia and the provinces most similar to it did not qualify for the donor pool either because they also opened economic zones in the same time window or because they are close neighbors (DKI Jakarta, West Java). As a robustness check, we re-ran the SCM while allowing DKI Jakarta and West Java in the donor pool. The synthetic Banten in this case includes the two above-mentioned provinces (with a combined weight of 32%) and approximates the true pre-treatment Banten better than before. At the same time, the positive treatment effect remains, albeit only for the first four post-treatment years (Figure A4).

5.4.2 Aceh 2014

In the Aceh case study the pre-treatment fit of the true and synthetic Ginis looks reasonably good (Figure 4), especially when taking into consideration that only three years of the Gini (2007, 2010 and 2013) out of the seven pre-treatment years were included in the optimization process. In terms of the other predictors, the synthetic control provides only a moderately good approximation of the true Aceh (Table A4). The fit is good for the literacy rate and the FDI stock but less so for other characteristics. In particular, the synthetic Aceh is more developed (less agricultural with a higher GDRP per capita) than the true Aceh was before 2014. This reflects the difficulty of finding good comparison provinces for Aceh – a relatively outlying province that was hit by a natural disaster not long ago.

Figure 4: Inequality - Aceh vs Synthetic Control

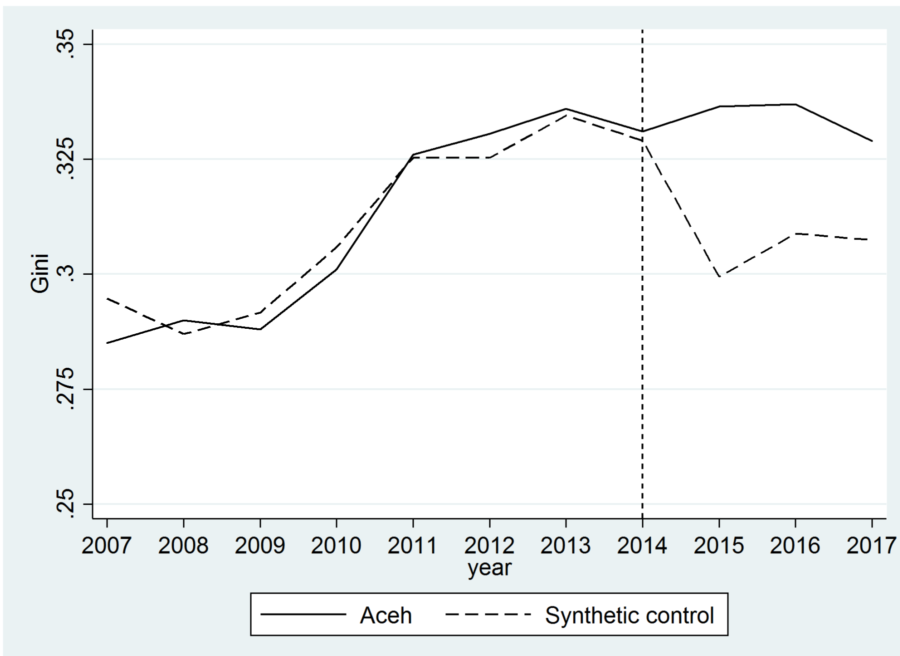


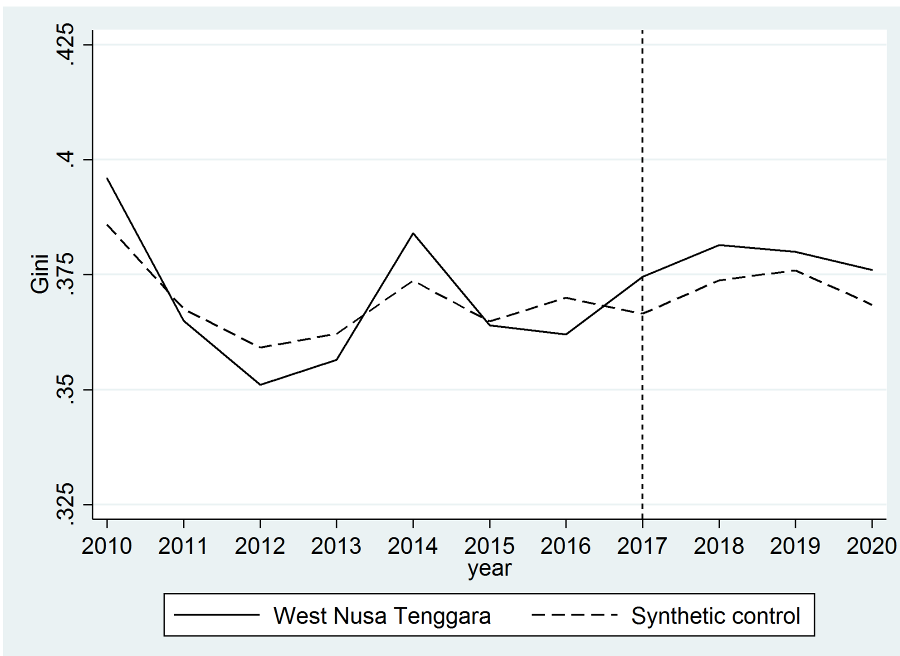
Figure 4 shows that income inequality in Aceh stayed stable after the treatment year of 2014, while income inequality in synthetic Aceh dropped, resulting in a positive treatment effect of a magnitude of 0.025 Gini points. One may suspect that an idiosyncratic drop in the Gini of one control province is responsible for this result, but it is not the case. The Gini fell in four out of the five donor provinces (Bangka-Belitung, Central Kalimantan, North Sulawesi, South Sumatra) during this period. In other words, the provinces most similar to Aceh experienced declines in their income inequality in the post-treatment period, while Aceh did not.

Having weighed the good fit of the pre-treatment Ginis against the above considerations, we interpret this result as a tentative evidence for a positive treatment effect.

5.4.3 West Nusa Tenggara 2017

The third case study provides an example of a situation when the SCM is of limited use. The pre-treatment income inequality in West Nusa Tenggara is only weakly matched by the synthetic control (Figure 5). As it turns out, it is not possible to find a combination of control provinces that is a good approximation of pre-treatment West Nusa Tenggara. Nevertheless, the performance with respect to the other predictors is relatively good (Table A5). The synthetic control approximates the pre-treatment GDP per capita and minimum wage especially well.

Figure 5: Inequality - West Nusa Tenggara vs Synthetic Control



All in all, no treatment effect of any sign is visible on Figure 5. The course of the true Gini after the treatment is quite stable, showing only a moderate increase. And without a well-performing synthetic control, it is almost impossible to identify an effect that is small at best. Hence, we conclude that there is no evidence that the Mandalika SEZ affected income inequality in West Nusa Tenggara.

5.5 Placebo analysis

In two of the three case studies we find some evidence for a positive treatment effect, meaning that income inequality of the treated province increased relative to the synthetic control following the treatment year. Of course, as in all statistical analyses, these estimates are subject to uncertainty. This section attempts to quantify this uncertainty by using the inferential technique developed by Abadie, Diamond and Hainmueller (2010).

We conduct placebo tests on provinces in the donor pool to evaluate the significance of the results for the treated province. If the post-treatment difference between the treated province and its synthetic control is larger than the difference for most of the placebo provinces, then we can conclude that the treatment had an effect. In these placebo exercises we keep every detail unchanged relative to the original case study, with the exception that the treated province (Banten, Aceh, or West Nusa Tenggara) is replaced by one of the provinces in the respective donor pools (and thus the number of provinces in the donor pool reduces from R to $R-1$).

Figures A5, A6 and A7 plot the differences between the placebos and their synthetic controls (grey lines) together with the original treatment effect for the truly treated province (thick black line). The figures for Banten and Aceh confirm the existence of a treatment effect for the first few post-treatment years. The treatment effect for Aceh is above most of the placebos during the entire four-year post-treatment period. Similarly, the treatment effect for Banten is larger than most placebos up to the fourth post-treatment year. Beyond this four-year horizon however the evidence for a treatment effect weakens.

6 Conclusion and policy recommendations

This study offers new empirical evidence from Indonesia on the local inequality consequences of economic zone policies. Our results based on panel regressions and synthetic control case studies suggest that economic zones can lead to rising income inequality within their province of location. This effect is relatively small on average and may be short-lived. In the case studies we find no evidence that the effect would persist longer than a four-year horizon. However, the moderate average effect may mask large regional variation, suggesting that the inequality implications of economic zone policies are dependent on local circumstances.

A systematic exploration of the determinants of the above relationship and the mechanisms involved is out of the scope of this study. Nevertheless, our investigation provides some insights into the relative importance of the channels mentioned in the Introduction. We suspect that the more likely explanation for why economic zone policies increase inequality is skill-biased growth and the resulting increase in the skill premium on wages. This is suggested by the regression-based evidence that lower unemployment is associated with higher income inequality in Indonesia. Further, we found no indication that the channel through land acquisions would play a significant role – at least not at this level of aggregation. On the one hand, our regression estimate is robust to controlling for between-province differences in the initial agricultural share. On the other hand, our third case study that features a dominantly agricultural province opening a SEZ for tourism did not show signs of rising income inequality. Finally, consistent with previous studies on Indonesia, our regression analysis provides no evidence that FDI in a province would affect local income inequality.

What policy advice can be derived from these results? In a world where economic development is highly dependent on the availability of human skills, access to quality education as well as vocational training (and re-training) opportunities are crucial, a point that has been emphasized by many (e.g. Castelló and Doménech, 2002). In what follows, we propose specific policies in this direction, building on the idea of corporate engagement and local community development.

For one, it is desirable to adopt policies that help local citizens and businesses participate meaningfully in the economic development of their neighborhoods. In this context, one can think of policies that provide education and vocational training to the poor and unskilled local population according to the needs of businesses in economic zones. Several countries such as China, Sri Lanka, Mexico, and Taiwan have established institutes that offer cooperative training programs. Improved skills help to find a job, become more productive and earn more (Aggarwal, 2007).

Domestic and foreign companies could also be encouraged to implement what is known as corporate social opportunity (CSO). CSO is different corporate social responsibility (CSR), which associates with one-time financial contributions and is often seen as a cost to companies. In contrast, CSO focuses on activities in which companies actively engage to the benefit of less-privileged social groups and, at the same time, co-create opportunities for both society and themselves. CSO allows companies to integrate their social activities into their core business and increase their competitiveness. Creating opportunities also requires collaboration with other parties such as local communities, government, universities, etc. to ensure inclusivity and define social needs (Moon, 2015).

Two practical examples are provided by the corporations Microsoft and Toyota, both of which operate in Indonesia. For example, Microsoft recognized the problem of insufficient supply of IT experts locally and organized IT training by providing computers, software and its own employees who taught on a voluntary basis. Many locals who were trained in this way were later also hired by Microsoft (Moon and Parc, 2019).[24] Another example

[24] This concept is also known as CSO for competitiveness, which goes beyond simply creating a good corporate image for stakeholders (Moon and Parc, 2019).

comes from Toyota, the Japanese car manufacturer, which has established an academy to train local Indonesians. The academy is known as Akademi Komunitas Toyota Indonesia (Community Academy of Toyota Indonesia) and is placed in West Java, the province with the highest number of economic zones.[25] Such initiatives could also be promoted in other – especially more remote – provinces with economic zones. It is often the case that companies face a shortage of skilled workers locally (Narula and Zhan, 2019) and must choose between recruiting workers from abroad or training the locals. When possible, local governments should encourage and incentivize these companies to choose the latter option.[26]

To sum up, economic zone policy has demonstrated its potential to promote economic growth. Our study directs attention to the question of how inclusive this growth is. Evidence of a rising income divide points to unequal distribution of gains and the poor and unskilled being left behind. As a policy recommendation, we emphasize the goal of equal access to quality education and promote the idea of corporate engagement in achiving this goal.

[25] The Academy's website is `http://www.akti.ac.id/home`.

[26] The dominance of foreign labor in economic zones raises the possibility of greater inequality, especially in terms of the socio-cultural dimension. One example is Cilegon in Banten province, Indonesia (Rahayuningsih, 2017).

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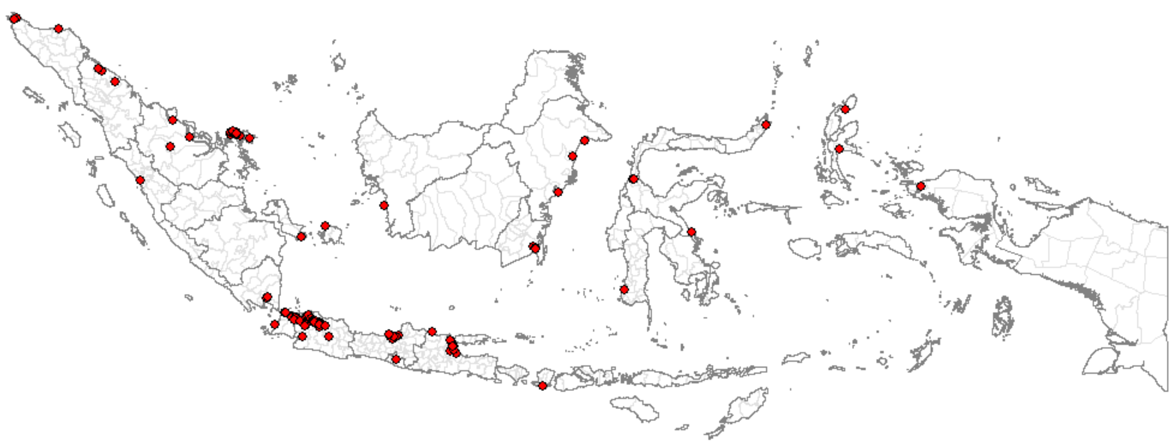
Appendix

A Further figures and tables

Figure A1: Location of economic zones in Indonesia



Note: Map of Indonesia showing provinces as areas bordered by dark grey lines. Red dots indicate the geocoded location of operating economic zones (industrial estates or SEZs) as of end-2020. Created by ArcGIS.

Figure A2: Estimated effect of base variables on time trend

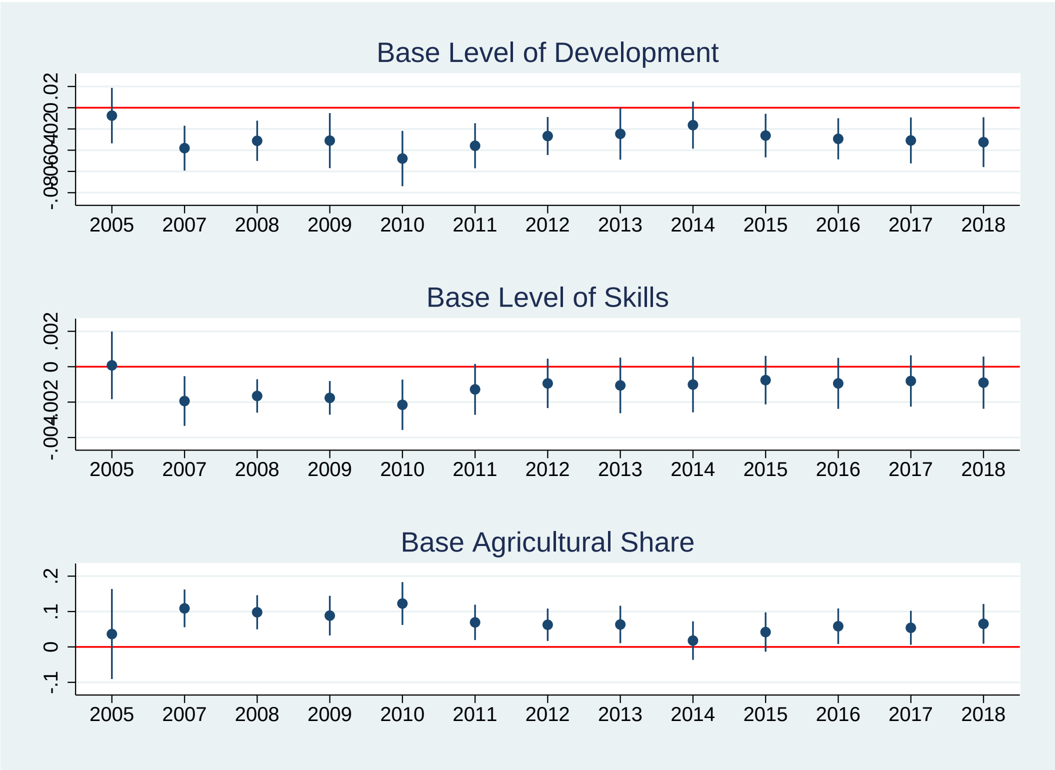
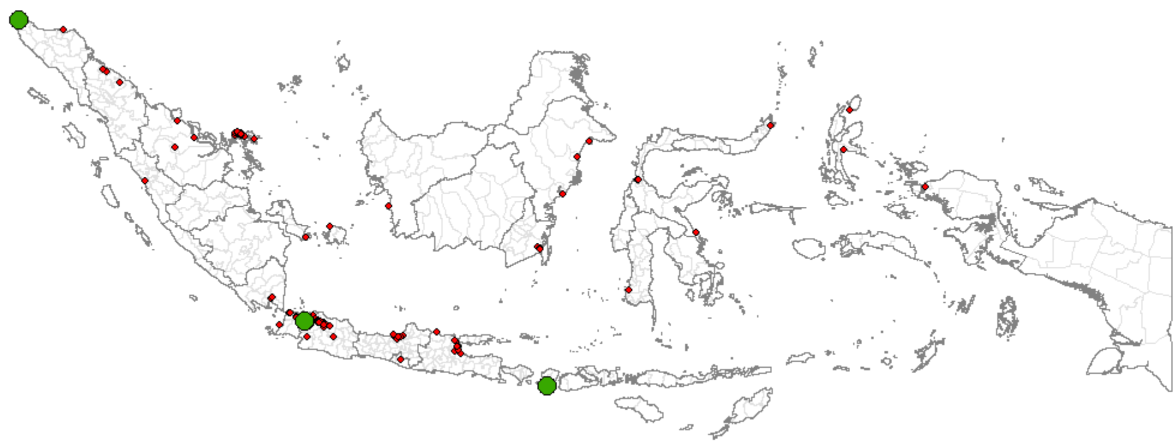


Figure A3: Location of the three SC cases



Note: Map of Indonesia showing provinces as areas bordered by dark grey lines. Red dots indicate the location of operating economic zones (industrial estates or SEZs) as of end-2020. The three larger green dots are the three zones selected for Synthetic Control case studies, from left to right: Perikanan Lampulo Industrial Estate, Taman Tekno BSD Industrial Estate, Mandalika SEZ. Created by ArcGIS.

Figure A4: Banten: Robustness with DKI Jakarta and West Java

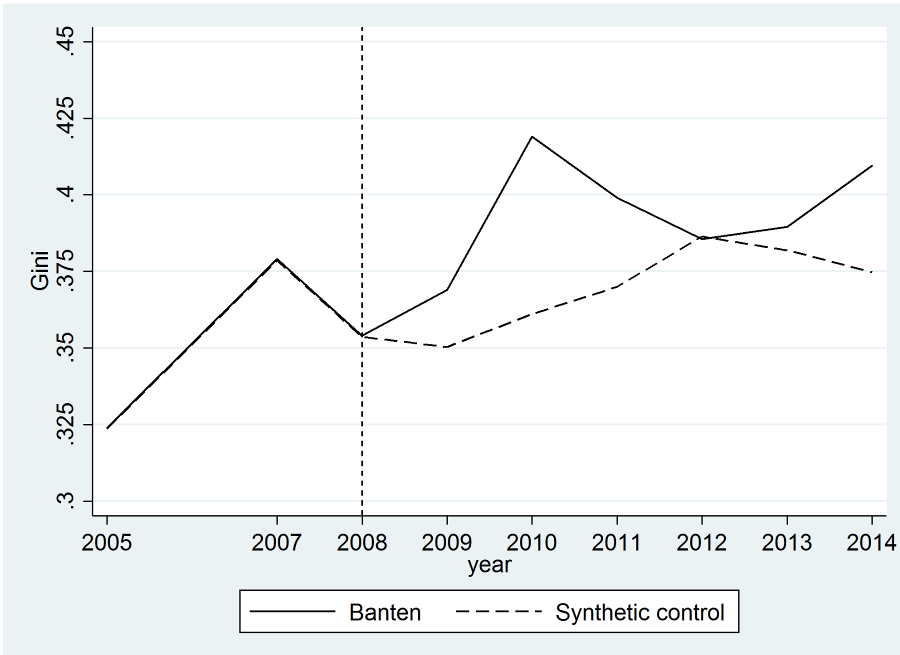


Figure A5: Placebo analysis - Banten

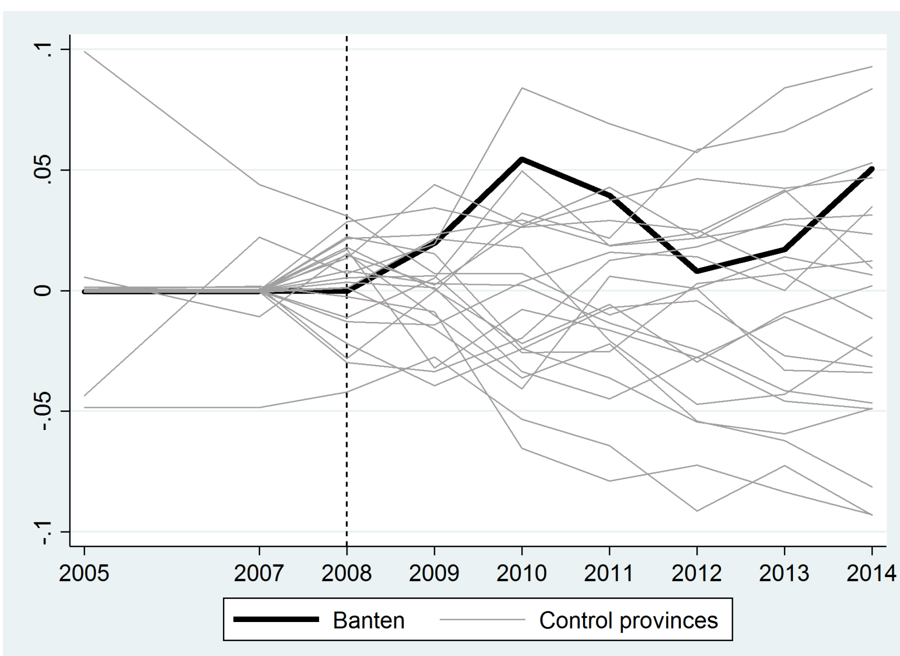


Figure A6: Placebo analysis - Aceh

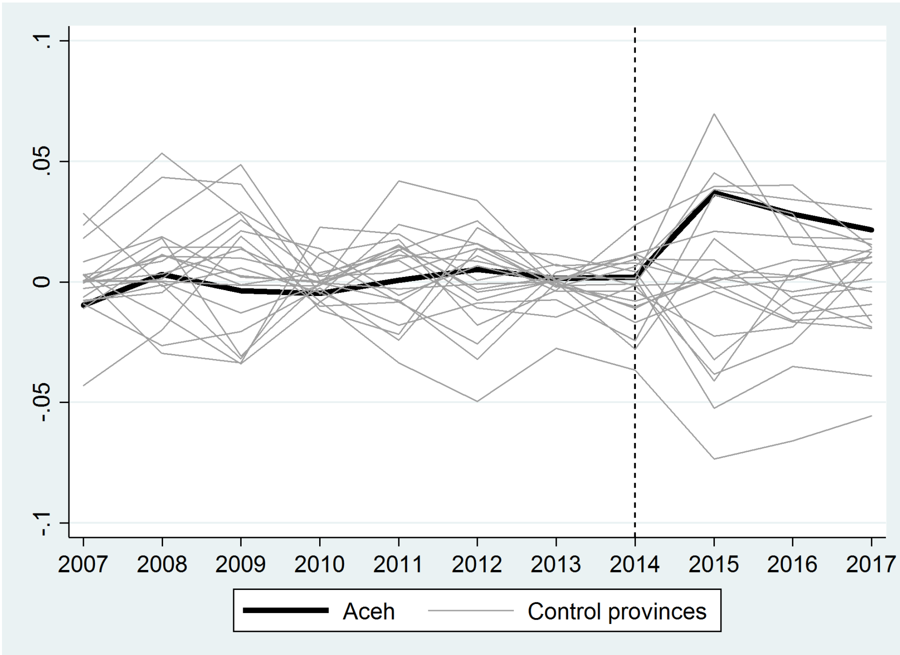


Figure A7: Placebo analysis - West Nusa Tenggara

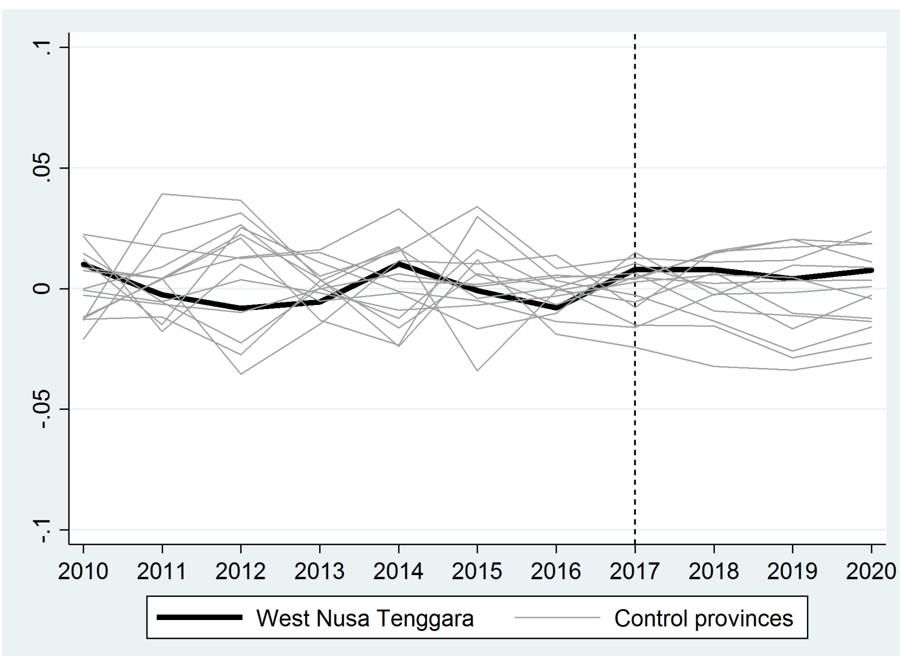


Table A1: Region-specific estimates: Java / non-Java

Depvar: Gini ratio	(1)	(2)	(3)
Number of zones × Java	0.00388***	0.00386***	0.00239*
	(0.000937)	(0.000926)	(0.00126)
Number of zones × Rest	-0.00211	-0.00345	-0.00486
	(0.00338)	(0.00373)	(0.00378)
GDRP (log)	✓	✓	✓
Other time-varying controls			✓
Province FEs	✓	✓	✓
Year effects	✓	✓	✓
Year × Base GDRP p.c.		✓	✓
Within R-squared	0.543	0.593	0.627
Observations	429	429	429

Note: Fixed-effects estimation of equation (2) on an unbalanced panel of 31 provinces over 14 years (2002, 2005, 2007-2018). Time-varying controls include the same set of variables as in column (4) of Table 3. All regressions include a dummy variable which is 1 for East Kalimantan from 2013 onward to control for its separation from North Kalimantan. Standard errors (in parentheses) are clustered by province.

Table A2: Donor pool and synthetic weights

		Banten 2008		Aceh 2014		West Nusa Tenggara 2017	
ID	Province	donor pool	SC weight	donor pool	SC weight	donor pool	SC weight
1	Aceh						
2	North Sumatra						
3	West Sumatra	1	0	1	0	1	0
4	Riau	1	0.091				
5	Jambi	1	0	1	0.027	1	0
6	South Sumatra	1	0	1	0.045	1	0
7	Bengkulu	1	0	1	0	1	0
8	Lampung	1	0.426	1	0		
9	Bangka-Belitung Island	1	0	1	0.596		
10	Riau Island						
11	DKI Jakarta			1	0	1	0
12	West Java						
13	Central Java						
14	DI Yogyakarta	1	0				
15	East Java						
16	Banten						
17	Bali	1	0.084	1	0	1	0
18	West Nusa Tenggara	1	0				
19	East Nusa Tenggara	1	0	1	0	1	0.319
20	West Kalimantan	1	0	1	0		
21	Central Kalimantan	1	0	1	0.256	1	0
22	South Kalimantan	1	0.310	1	0		
23	East Kalimantan						
24	North Kalimantan						
25	North Sulawesi	1	0	1	0.076		
26	Central Sulawesi	1	0				
27	South Sulawesi	1	0	1	0	1	0
28	Southeast Sulawesi	1	0	1	0	1	0.305
29	Gorontalo	1	0	1	0	1	0
30	West Sulawesi			1	0	1	0.376
31	Maluku	1	0	1	0	1	0
32	North Maluku	1	0	1	0		
33	West Papua			1	0		
34	Papua	1	0.090	1	0	1	0
	Total	22	1.000	21	1.000	14	1.000

Table A3: Predictors of inequality - Banten

	Banten		Average of
	Treated	Synthetic	donors
GDRP (log)	18.982	18.041	17.789
Poverty gap (index)	1.727	3.346	3.363
Literacy rate (in population of age 15+)	0.953	0.913	0.908
Enrollment ratio in secondary school (net, %)	39.670	39.571	42.611
Minimum wage (log)	13.402	13.264	13.249
Unemployment rate + Underemployment rate	0.392	0.411	0.443
Gini 2005	0.324	0.324	0.326
Gini 2007	0.379	0.379	0.352

Note: The numbers are annual averages over the period 2005-2007, unless indicated otherwise. The last column contains population-weighted averages of donor pool provinces. RMSPE=0.0000028.

Table A4: Predictors of inequality - Aceh

	Aceh		Average of
	Treated	Synthetic	donors
Population density (log)	4.361	3.955	5.139
GDRP per capita (log)	10.037	10.217	10.148
Literacy rate (in population of age 15+)	0.960	0.963	0.931
Agriculture's share in employment	0.486	0.398	0.456
Cumulated FDI per capita	0.254	2.297	6.141
Gini 2007	0.285	0.295	0.355
Gini 2010	0.301	0.306	0.362
Gini 2013	0.336	0.335	0.386

Note: The numbers are annual averages over the period 2007-2013, unless indicated otherwise. The last column contains population-weighted averages of donor pool provinces. RMSPE=0.0046615.

Table A5: Predictors of inequality - West Nusa Tenggara

	West Nusa Tenggara		Average of
	Treated	Synthetic	donors
GDRP per capita (log)	9.762	9.877	10.543
Poverty gap (index)	3.303	2.688	2.116
Literacy rate (in population of age 15+)	0.849	0.910	0.936
Government expediture (share in GDP)	0.158	0.207	0.150
Minimum wage (log)	13.930	13.978	14.168
Gini 2010	0.396	0.386	0.363
Gini 2013	0.357	0.362	0.393
Gini 2016	0.362	0.370	0.373

Note: The numbers are annual averages over the period 2010-2016, unless indicated otherwise. The last column contains population-weighted averages of donor pool provinces. RMSPE=0.0074335.