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Assessing the Impact of the Indian Ocean Tsunami on the Economy: Evidence from Indonesia and Thailand 7

Inggrid,†& Siana Halim,‡ and Indriati Njoto Bisono‡ Abstract— Recent research in developed countries shows an adverse effect of natural disasters on the economy. This paper aims at examining whether this is also relevant for developing countries. Applying a counterfactual approach to provincial data for Indonesia and Thailand, we find that the Indian Ocean tsunami of 2004 negatively affects per capita gross domestic product (GDP) of the exposed provinces. It is also shown that the effect is heterogeneous within the country. These results seem straightforward to reconcile with previous evidence using developed countries data.

Keywords—natural disaster, economic impact, developing country. I. INTRODUCTION A SMALL but growing literature has been devoted to study the economic consequences of disasters with the evolution of gross domestic product (GDP) as the central topic. The other common characteristic is the level of analysis focusing on cross-country studies. Intriguingly, existing empirical studies produce mixed-results. Following neoclassical growth frameworks, natural disasters are predicted to have a positive effect on the GDP trajectory. In contrast, endogenous growth models provide less clear-cut explanation of disaster effects. A class of endogenous growth models à la the Schumpeterian creative destruction process reaches an agreement with the neoclassical theory. Several earlier works seem to support favorable effects of natural disasters [1]-[3].

Yet, the AK-type endogenous growth models 4

predict trivial impacts of disasters on the growth rate even

though the economy that experiences a destruction of the capital stock will never go back to its pre-disaster **growth** 4

path. Another variant of the endogenous growth theory with a production function that exhibits increasing returns to scale * This research was made possible by funding from the Indonesian Directorate General of Higher Education (DIKTI) under SP-DIPA- 023.04.2.415015/2014. †

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inggrid@peter.petra.ac.id). posits that natural disasters lead to adverse and permanent effects on growth trajectories [4]-[5]. However, conducting cross-country studies to evaluate the actual impact of natural hazards gives rise to two main problems. First, from growth theory, this means that they impose the strong assumption of parameter homogeneity [6]. Therefore, the effects of population growth, physical and human capital, as well as the initial level of 16

income on income growth are the same for all countries in the analysis. In fact, this assumption is very strong and unrealistic. For instance, it is very unlikely that different types of natural disasters produce similar effect on the economy. Second, country-level studies unable to capture the spatial distributional effect of the disaster. This paper seeks to fill the gap by investigating the causal effect of the tsunami catastrophic disaster in 2004 on the regional economy of Indonesia and Thailand, the two most affected countries. It was 26 December 2004 at 00.59 GMT (just before 08.00 a.m. Jakarta time), when a powerful earthquake with magnitude of 9.0 on the Richter scale hit Sumatra Island of western Indonesia. The earthquake subsequently generated devastating tsunami waves, yielding the tallest wave as high as 24.4 meters. The tsunami totally slammed Aceh Province of Sumatra, the closest area to the epicenter of the earthquake, whereas Nias Island of North Sumatra Province was less affected. The successive tsunami moved to the west to hit coastal areas of the other Asia countries (India, Malaysia, Maldives, Myanmar Srilanka, and Thailand) and several African countries (Kenya, Somalia, and Tanzania). In Thailand, the impacts of the tsunami were more pronounced in the southern part, especially Phuket, Krabi, Phang Nga, Trang, Ranong, and Satun [7]. Looking at the data, it was reported that Indonesia experienced by far the highest number of fatalities than Thailand (over 165,000 versus 8,300) representing about 70% of all deaths. Although these countries suffered from the misery, the macroeconomic impact on Indonesia and Thailand in 2005 was predicted to be small because Aceh's GDP was approximately 4% of Indonesian GDP whereas the combined six provinces of Thailand

accounted for only 2. 7% of the national GDP 18

(The Economist Intelligence Unit, 2005). Yet, preliminary findings reported that the tsunami had a sizeable impact on the regional economy of Aceh in Indonesia and Phuket and Krabi in Thailand [8]-[9]. We use the synthetic control method (SCM) to estimate our causal of interest [10]-[11]. SCM is an extension of the original difference-in-differences (DiD) but it is less stringent with respect to the identical trend assumption and it allows for the presence of unobservable time-variant provinces characteristics. The method is suitable in our case since the tsunami is considered as a large shock influencing a single province. This current work enriches fairly limited study available on

the economics of natural disasters in developing countries. The findings of 12

our work also complement a recent study based on developed country data [12] and corroborate disaster theories about a non-linear relationship between a country's income per capita disaster shocks.

This paper proceeds as follows. In Section 2, we give an overview of estimating the 11 distributional effect of the tsunami by utilizing SCM. Section 3

presents the main **findings of the** paper. The last **section concludes. II.** 20

SYNTHETIC CONTROL METHODS We are interested in examining whether the Asian tsunami

has a substantial influence **on the** provincial **GDP per capita** 19

of Indonesia (i.e. Aceh and North Sumatra) and Thailand (i.e. Phuket, Krabi, Phang Nga, Trang, Ranong, and Satun). The fundamental problem we have is to find an unexposed province that best reproduces the characteristics of those exposed provinces. Given that none of the other comparison provinces follow the identical time trends as the provinces of interest; our strategy is to take a weighted average of all potential comparison provinces as a control group of the affected provinces. Therefore, the economic effect of the disaster is estimated through the difference in the regional GDP per capita between the two groups after the tsunami. This method is well-known as the synthetic control method (SCM). We formalize the concept of the synthetic control method as follows. Suppose that we observe n provinces (n =24 provinces for Indonesia1 and n =35 provinces for Thailand2) for the period t =1995,…,2004,…,2012. Let i =1 be the exposed province, and i =2,…, n be the other provinces that serve as the potential 1 Since the introduction of the Regional Autonomy Law in 1999, the number of provinces has been proliferating in Indonesia. Maluku and Papua have split into two provinces since 1999. The new provinces are North Maluku and West Papua. A year later, the other three provinces were established, i.e. Bangka Belitung

of South Sumatra, Banten of West Java, and **Gorontalo of North Sulawesi.** Riau **and** 9

South Sulawesi were separated to Kepulauan Riau in 2002 and West Sulawesi in 2004 respectively. The latest was North Kalimantan which was previously the part of East Kalimantan before 2012. Overall, there were 34 provinces in 2012. To maintain consistency, we amalgamate these proliferated provinces with their original provinces and leave us with 26 provinces. However, we exclude DKI Jakarta and East Kalimantan from the donor pool since these two provinces have extremely high per capita GDP among the other provinces. 2 Thailand has 76 provinces and is geographically divided to seven regions, i.e. Bangkok and Vicinities (6

provinces), Northern (17 provinces), North eastern (19 provinces), Southern (14 provinces), 10

Eastern (8 provinces), Western (6 provinces), and Central (6 provinces). We only use the four last regions in the analysis due to their similar socioeconomic characteristics. control group or the donor pool for the affected province. Here, we let T0 =2004 be the year when the tsunami struck Indonesia and Thailand. We denote YitI as the regional GDP per capita in the presence of the tsunami, while YitN is the regional GDP per capita if the tsunami had not occurred. It is generally acceptable to assume that the disaster does not have any effects on the outcome prior to its occurrence at time T0 . Hence, YitI =YitN for t∈[0,…, T0 -1]. The economic

effect of the tsunami **for** province **i at time t** is written as: **?it** 6

? YitI ? YitN (1) We also have Dit , the binary variable

that takes a **value** of **one if** province **i is exposed to the** tsunami **at time t and zero otherwise.** We can observe **the** post-tsunami **outcome for** province **i at time t** as: **Yit** 1

?YitN ??itDit (2) For each model, we assume that the only first province in Indonesia and Thailand hit by the tsunami after T0 . Therefore, = {1 0 = ℎ1 > 0 Our goal is to estimate ?it for the eight affected provinces (i =1) and for all t >T0 , or: ?1t ? Y1It ? Y1Nt ? Y1t ? Y1Nt (3) The above equation implies that Y1It is observed in the period 2005-2012, whereas Y1t is unobserved. We need to N estimate Y1Nt which is the counterfactual of the exposed provinces or the synthetic control units. It is shown in [12] that: YItN ??t ??tZi

??t?i ??it (4) **where ?t is an** unobserved **common** time-dependent **factor,** 2

?t is a vector of unobserved **parameters,** Zi **is a vector of** 2

observed covariates for important ingredients for a growing GDP that is not affected by the tsunami, ?t is unknown common factors, ?i is a province-specific unobservable, and ?it are the error terms which represent

unobserved transitory shocks at the level 1

of province (E(?it 0 for all i and t).) ? Forconstructingthesyntheticcontrolunit,wedefinea(rx1)

vector of weights W ?(w2,.... wn)' **such that** wi ?0for i **=2,…,** 1

n and ?ni?2 wi ?

1. Each value of W indicates **a potential synthetic control** 2

unit for each exposed provinces. We thus state the outcome for each synthetic control as: n n n n ?wiYit ??

t ??t?wiZi ??t?wi?i ??wi?it

(5) i?2 i?2 i?2 i?2 14

We need to choose a set of weights (w2* ,...., w*n)' that best reproduces pre-tsunami characteristics of the exposed provinces such that: ? w*iYi1 ? Y11,..., ? w*iYiT0 1T0 and ? w*iZi n n n ? Y ? Z

1 (6) i?2 i? 2 i?2 21

It is proved that, as long as the condition in (6) holds and the number of pre-tsunami observations is large as compared with the level of the transitory shocks [11], then Y1tN ? ? w*iYit n (7) i?2 Ultimately, the estimator for ?1t for t∈[T0 +1,…, T] is given by ?ˆ1t ? Y1t ? ?1n?2 wi*Yit (8) It should be noted that equation (2) can hold precisely under the condition (Y11,...,Y1T0,Z1')Iˆ{(Y21,...,Y2T0,Z2'),.....,(Yi?11,.....,Yi?1T0,Zi'?1)} However, in some cases, it is often possible to select the synthetic control W*to approximately satisfy condition (6).

To assess the validity **of our** causal results, **we conduct a series of placebo** 1

tests aimed at testing the underlying identification assumptions of our models. However, our falsification tests must depend on permutation inference since the small samples used in SCM. III. RESULTS AND DISCUSSION The essence of SCM is to construct a counterfactual unit or

a synthetic control unit that closely replicates **the** pre-tsunami characteristics **of the** 17

affected provinces. This is defined as a weighted average of unexposed provinces whose per capita GDP is akin to the affected provinces if it had not been hit by the tsunami. Figure 1 shows that the levels and trends of

per capita GDP **between the** exposed province **and the synthetic control** 5

unit in all eight cases are very similar.3 The values of per GDP ingredients of the exposed provinces before the onset of the tsunami do not diverge significantly to those of the synthetic units.4 These findings suggest that the current exercises satisfy the identifying assumptions of SCM. The exposed and synthetic provinces are fairly comparable after the tsunami period. What about the economic impacts of the tsunami? Figure 1 clearly shows that the tsunami has a negative effect on per capita GDP in Aceh, Phuket, Krabi, Phang Nga, and Satun, whereas it turns to be small and positive in North Sumatra, Trang, and Ranong. However, it is should be noted that between Aceh and Phuket, the two most affected provinces, the evolution of per capita GDP is remarkably different. Aceh appears to experience a persistent decline in its GDP per capita while Phuket is able to recover from the catastrophic disaster and moves toward an upward trend. Table 1 presents summary statistics of the per capita GDP gaps between the affected provinces and the synthetic units. Given the level of Aceh's actual GDP per capita, per capita GDP in this province seems to be 16.24% lower than in the 3 We use a different length of the pre-tsunami period

to minimize the root mean squared prediction error (RMSPE) 13

for each case because per capita GDP of some province fluctuated in the late 1990s. 4 The predictor balance tests available upon request. synthetic counterfactual in 2005 and -27.02% on average during the period from the occurrence of the tsunami. Looking at Phuket, per capita GDP is 21.95% lower in 2005 and 3.08% lower on average. In general, the table also suggests that the economic effect of the tsunami is larger in Indonesia than Thailand (reducing per capita GDP by 7.31% and 4.98% in 2005 respectively). To test the validity of our results, we perform a four different type of placebo exercises (i.e. placebo tests among untreated unit, placebo tests in time, treatment extremity test, and leave-one-out tests) to falsify several underlying assumptions. These placebos should not respond uniformly to false interventions as the real treated unit does to the true intervention if the causal effect is unquestionable. These falsification tests further strengthen our findings.5 TABLE I SUMMARY OF THE TSUNAMI IMPACT IN INDONESIA AND THAILAND 2005 Average Gap % Gap % Indonesia -816.21 -7.31 -1,245.45 -10.36 Aceh -1,744.82 -16.24 -3,014.25 -27.02 North Sumatra 112.40 1.62 523.36 6.30 Thailand -9,285.87 -4.98 -1,534.04 -1.17 Phuket -49,445.71 -21.95 -6,757.41 -3.08 Krabi -8,863.03 -11.31 -446.27 -0.63 Phang Nga -732.29 -0.91 4,797.00 5.30 Trang 988.23 1.52 -4,773.15 -6.48 Ranong 2,392.44 2.86 -921.82 -0.80 Satun -54.84 -0.08 -1,102.58 -1.34 Notes: Gap is the

difference in per capita GRDP **between the** exposed province **and the synthetic control** 5

unit (in 1,000 Rupiah for Indonesia and in Baht for Thailand). % is the ratio of Gap to per capita GRDP of the synthetic control. Average is averaged over the post-tsunami period. IV. CONCLUSION We investigate the effects of the regional economic exposure to a catastrophic disaster in Indonesia and Thailand

in the aftermath of the 2004 Indian Ocean tsunami. 15

We find that Aceh, Phuket, Krabi, and Phang Nga experience a nontrivial decline in their per capita GDP, whereas the economy of North Sumatra, Trang, Ranong and Satun are less affected.

To the best of our knowledge, this **is** the first **study** 6

applying a-quasi-experimental strategy and focusing exclusively on macroeconomic data from developing countries to identify the causal effects of a large natural disaster on the short- and the medium-term of income per capita. However, a major limitation of the macroeconomic framework as our current work is that it does not give a detailed explanation of the total welfare loss from the disaster. The study of microeconomic data apparently helps to identify utility losses together with many other multifaceted dimensions (such as education, health, and poverty). This analysis is especially suitable for developing countries, like Indonesia and Thailand because the 5 Results available upon request. Fig. 1 Per capita regional GDP (in log): affected provinces and synthetic control units consequences of large disasters are more serious, but there is no adequate insurance coverage to protect households from such extreme events. For this reason, an investigation of the distributional impacts as well as insurance mechanisms against the economic costs of natural disasters deserves further attention in the future research.

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APPENDIX A: DATA DESCRIPTION We describe the data used in the analysis and provide sources. The data are at the provincial level for the period 1995-2012. Indonesia: Per capita regional GDP (millions of Rupiah). Source: Central Bureau of Statistics (BPS). The data are obtained by dividing the value of GDP in a particular province by its total population. Sectoral shares (%). Source: Central Bureau of Statistics (BPS). It consists of the value added of 9 economic sector, that is, agriculture, hunting, forestry, and fishing, mining and quarrying, manufacturing, electricity, gas, and water, construction, trade, hotel, and restaurant, transportation and telecommunication, finance, real estate, and services. The share of each sector is obtained by dividing the value added of each sector by the total provincial GDP. Population density (persons per square kilometer). Source: Central Bureau of Statistics (BPS). It is calculated as total population divided by land area in kilometre square. Human capital (%).Source: Central Bureau of Statistics (BPS). It includes educational attainment of the population (i.e. adult literacy rates, primary school, junior high school, senior high school, and university). Physical capital (%).Source: Central Bureau of Statistics (BPS). It is the share of fixed capital formation in the provincial GDP. Thailand: Per capita regional GDP (millions of Bath). Source: National Statistical Office of Thailand (NSO). The data are obtained by dividing the value of GDP in a particular province by its total population. Sectoral shares (%).Source: National Statistical Office of Thailand (NSO). It consists of the value added of 16 economic sector, that is, agriculture, mining and quarrying, manufacturing, electricity, gas and water supply, construction, wholesale and retail trade, hotels and restaurants, transport, storage and communications, financial intermediation, real estate, renting and business activities, public administration and defence; compulsory social security, education, health and social work, other community, social and personal service activities, and private households with employed persons Population density (persons per square kilometer). Source: Ministry of Interior. It is calculated as total population divided by land area in kilometre square. Human capital (%).Source: National Statistical Office of Thailand (NSO). It includes educational attainment of the population (i.e. preschool, primary school, junior high school, senior high school, and university). Credit to GDP ratio (%).Source: Bank of Thailand (BoT). It is the ratio of domestic credit provided by financial sector to provincial GDP. Inggrid is a lecturer and researcher in the Department of Business Management, Faculty of Economics, Petra Christian University, Indonesia. She did her postgraduate degree in economics at Uppsala University, Sweden. She is interested in program evaluation (with main focus on impact evaluation), poverty and inequality, human capital formation, and economic modeling. Siana Halim is a lecturer and researcher in the Department of Industrial Engineering, Faculty of Industrial Technology, Petra Christian University, Indonesia. She received her Ph.D. in statistics from Technische Universität Kaiserslautern, Germany, in 2005. Her research interests are statistical modeling, data analysis, and non-parametric statistics. Indriati Njoto Bisono is a lecturer and researcher in the Department of Industrial Engineering, Faculty of Industrial Technology, Petra Christian University, Indonesia. She has been doing her Ph.D. in applied statistics at the University of Melbourne, Australia. Her teaching and research interest include Statistical Modeling and Design of Experiment.