Remittances after natural disasters:
Evidence from the 2004 Indian tsunami

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August 2014

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Evidence from the 2004 Indian tsunami[#]

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Abstract: We examine the impact of the 2004 Indian tsunami on international remittance transfers using aggregate country data and synthetic control methodology. This procedure implies identifying the causal impact of the disaster by comparing the share of remittances to GDP in Indonesia, the country most affected by the shock, with a counterfactual group constructed using synthetic controls of countries that were not affected by the tsunami but that had a very similar pre-shock trend in international remittance flows. Our results indicate a large impact on remittances in Indonesia just after the tsunami, with 1.35 additional points in share of remittances to GDP in 2005 (compared to the synthetic control group). However, the gap in remittances observed between Indonesia and the synthetic control decreased steadily over the succeeding years and amounted to 0.5 percentage points in 2011.

Keywords: natural disasters, remittances, synthetic control, Indonesia

JEL Classification: F24, Q54

1. Introduction

In recent years, a growing number of papers have attempted to assess how natural disasters (such as earthquakes, tsunamis, hurricanes or floods) impact different economies and, in particular, their consequences on international trade, financial flows and growth rates (Cavallo et al., 2013; Strobel, 2013; Felbermayr and Grösch, 2013), fertility and population dynamics (Finlay, 2009), human capital, poverty and income distribution (Karim and Noy, 2013).

Our paper relates to another aspect that has been recently addressed in this literature: migration and remittance flows in the aftermath of natural disasters (Boustan et al., 2012; Halliday, 2012). Establishing a causal effect of a transitory income shock induced by the largely unpredictable nature of natural disasters on the flow of international migrant remittances has proven to be a challenging task (Arezki and Bruckner, 2012). One issue largely acknowledged in this literature is the simultaneity problem between income and remittances.

To address this concern, recent papers have used the instrumental variable technique. For example, Yang (2008) employs a time-varying storm index to show that increased hurricane exposure is associated with greater remittance flows in poorer developing countries that may reflect both ex-ante risk sharing and ex-post consumption smoothing.[1] Similarly, Yang and Choi (2007) utilize rainfall shocks as instrument for changes in household income in the Philippines and find that income shocks lead to changes in remittances in the opposite direction, consistent with an insurance motivation. Using annual variations in rainfall across Sub-Saharan African countries as an exogenous source of (transitory) income shocks, Arezki and Brückner (2012) find no contemporaneous effect on remittances, but they show that the marginal effect of these shocks is significantly decreasing in the share of domestic credit to GDP.[2]

To assess the consequences of a natural disaster on a given outcome, ideally, one would like to have access to household data tracking individuals both before and after the shock. However, this causes two main challenges for developing countries. On the one hand, this would require collecting "preventively" individual data every year in all countries potentially subject to such natural disasters, so that these households could be re-interviewed later. On the other hand, the natural disaster is expected to lead to substantial human and economic loss, meaning that tracking the ex-ante at-risk individuals may be a fruitless operation. Selective attrition because of decease or

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[1] Remittance transfers from overseas migrants could be due to ex-ante risk sharing agreements (through some reciprocal transfers) or a simple desire to assist ex-post those affected (due to altruism or reciprocity). Another strand of papers address the risk-coping mechanisms by the rural households to cope with shocks in rural communities and find evidence in line with a consumption smoothing mechanism (Townsend, 1995; Udry, 1994; Ligon et al., 2002).

[2] Using micro-level data, the literature has largely reached a consensus that migration and remittances form a livelihood strategy by which households insure against shocks in regions more prone to natural disasters (Mohapatra et al., 2012).

migration will undoubtedly bias the measurement of the adverse outcome of the natural disaster when using micro data collected at the individual or household level.

The purpose of our contribution is to investigate the causal effect of a natural disaster on remittance inflows using aggregate data. Specifically, we will focus on the effect of the 2004 Indonesian tsunami on international remittance transfers. This case study is particularly interesting for at least two reasons. First, the 2004 Indian tsunami was one of the deadliest natural disasters recorded in history, with over 230,000 causalities and massive community destructions across affected coastlines. So, if the tsunami had any effect on the transfer behavior of migrants, then we should observe some change in the remittance inflows after the tsunami. We will look at Indonesia in particular, as this was the country hardest hit, with a death toll reaching 225,000 causalities and an estimated 655,000 homeless.[3] Second, the tsunami occurred on Sunday, December 26th, 2004, so that any adjustment in remittances would only be observed in 2005.[4]

From a methodological viewpoint, the problem that we face in estimating the causal effect of the tsunami disaster on remittances is that of finding an appropriate counterfactual, i.e., what would have been the remittance transfers in Indonesia in the absence of the tsunami natural disaster. Because we use aggregate data at the country level, we rely on the synthetic control approach that was originally proposed in Abadie and Gardeazabal (2003) and further investigated in Abadie et al. (2010; 2014).[5] This estimator provides a control group comprised of a set of countries that were not affected by the tsunami but that had a very similar trend in international remittance inflows compared to that of Indonesia before the shock. The weights of the selected countries forming the synthetic Indonesia are endogenous.

We implement the synthetic control estimator using the World Bank Development Indicators over the period 1995-2011. Our results indicate a large impact from the tsunami on remittances: 1.35 additional points in share of remittances to GDP observed in 2005 in Indonesia (compared to the synthetic control group) can be interpreted as the causal impact of the tsunami. To assess the validity of our results, we run a set of placebo exercises and apply a similar weighting approach to a set of countries from which we extract our control group and which, by definition, were not affected by the shock. For the sake of comparison, we also consider the classical difference-in-differences (DID) approach with various forms of unobserved heterogeneity to assess how our variable of interest has changed following the shock for treated and control countries. Our results

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[3]   Sources :   http://en.wikipedia.org/wiki/Effect_of_the_2004_Indian_Ocean_earthquake_on_Indonesia   and http://en.wikipedia.org/wiki/2004_Indian_Ocean_earthquake_and_tsunami

[4] The timing of the natural disaster is very important for our identification strategy because the 2004 remittances are expected to be uncontaminated in Indonesia as the tsunami occurred at the very end of the year.

[5] This method has been used very recently by Cavallo et al. (2013) to assess the causal impact of natural disasters on economic growth and by Lynham et al. (2012) to assess the long-term impact of the 1960 tsunami in Hawaii on population and employment dynamics.

indicate that the synthetic control approach is a central tool to assess the consequences (in terms of magnitude and direction) of an exogenous shock such as a natural disaster using aggregate data.[6]

The remainder of our paper is organized as follows. Section 2 describes the data and provides some basic intuition for the synthetic control approach that is further detailed in Section 3. Section 4 describes our main results, while several robustness checks are presented in Section 5. Finally, Section 6 concludes the paper.

2. Data

To understand whether international remittances responded to the 2004 Indian tsunami, we use the World Development Indicators (WDI) database, which is publicly available from the World Bank.[7] The dependent variable we consider for our empirical analysis is the amount of international remittances received as a percentage of GDP. This indicator has been frequently used in the literature on the determinants of remittances (see, for instance, Amuedo-Dorantes and Pozo, 2004; Arezki and Brückner, 2012; Ziesemer, 2012; Termos et al., 2013; Gnangnon, 2014). As emphasized in Chami et al. (2008), the WDI indicator is the most appropriate when conducting any econometric analysis regarding remittance behavior.

In the WDI data set, personal remittances are defined as the sum of personal transfers and the compensation of employees. Personal transfers include all current transfers in-kind or cash received by resident households from non-resident households, but exclude internal transfers (between resident households). The compensation of employees includes income of border, seasonal, and other short-term workers employed in an economy where they are not a resident and of residents employed by nonresident entities.[8] Because of data restrictions, we analyze the flow of international remittances for the period 1995 to 2011, 10 years before the tsunami disaster in late December 2004 and 7 years after.

The two countries most affected by the Indian tsunami were Indonesia and Sri Lanka, followed by Thailand and India. Over the 1995-2011 period, the average share of remittances as a percentage of GDP in these countries was 2.85% in India, 1.02% in Thailand, 7.36% in Sri Lanka, and 0.91% in Indonesia. Interestingly, the coefficients of variation in remittances are very different: 0.1 in Sri Lanka, approximately 0.2 in Thailand and India, and 0.5 in Indonesia, suggesting more dispersion in remittances for the latter country. In Figure 1, we show the trends in remittances between 1995 and 2011 for the four selected countries. To make the comparison easier, we represent the ratio of

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[6] The use of aggregate data does not allow us to understand the motives behind the remittance transfers.

[7] These are the most accurate global development data available worldwide that cover the period ranging from 1960 to 2012. The WDI data set is available online at http://data.worldbank.org/data-catalog/world-development-indicators. We have used the WDI available in 2013. In 2014, the variable measuring remittances as a percentage of GDP is actually missing for a few important countries near Indonesia (such as Papua New Guinea, for instance), so we cannot use this year.

[8] See http://data.worldbank.org/indicator/BX.TRF.PWKR.CD.DT.

the contribution of remittances to GDP to the country-specific remittance contribution as measured in 1995. The figure indicates contrasting patterns.

Insert Figure 1

For Indonesia, we observe a large increase in the contribution of remittances to GDP in 1998, with more than three times the 1995 level, most likely because of the 1997-1998 Asian financial crisis. After a flat period from 2000 to 2004, the share of remittances in the GDP suddenly exploded in 2005 (about six times the level observed in 1995), before declining steadily at the end of the period. Our assumption is that the 2005 peak is the result of the end of the December 2004 tsunami disaster. Because our dependent variable is the ratio of remittances to GDP, one concern with this interpretation is that the peak does not stem from an increase of transfers sent by migrants living abroad but from a decrease in the GDP. When considering the PPP GDP expressed in constant 2005 international dollars, we observe instead a regular increase in Indonesia since 1999 (Figure 2): between 2002 and 2011, the annual growth rate of GDP has fluctuated between 4.5% and 6.5%.

Insert Figure 2

At the same time, for the other countries, we observe no change in the share of remittances in the GDP in 2005. In Thailand, we even observe a fall in the contribution of remittances to GDP from 2005 to 2008: compared to its level in 2004, the contribution of remittances to GDP was approximately one-third lower in 2005. In Sri Lanka, there is a slight increase in remittances from 7.69% in 2004 to 8.09% in 2005 that falls afterwards to 7.66% in 2006. Finally, there is no particular effect at the time of the tsunami in India; the remittance profile slightly increases all over the period. An explanation of these differences could lie in the stock of migrants living abroad and in the share of emigrants in the total population. According to the WDI data, the total number of immigrants less the annual number of emigrants in 2002 was -525,809 in Indonesia, -100,001 in Sri Lanka, 1,102,862 in Thailand and -1,923,245 in India.[9]

The graphical evidence shown above suggests a clear link between the tsunami disaster and the increase in remittances in Indonesia, while the situation seems unaffected in the neighboring countries, which were also affected by the disaster. However, to interpret the 2005 sharp change in remittances in Indonesia as the causal response to the tsunami disaster, we would like to know what the situation in Indonesia in terms of remittances would have been had the disaster not occurred. By definition, this counterfactual scenario is not observable. With country level data, finding appropriate controls remains difficult. Ideally, we would like to be able to compare Indonesia with another country, with exactly the same trend in international remittances received before 2004 but not

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[9] In the WDI data set, data for net migration are reported every 5 years. In 2000, Indonesia and India had about 900 emigrants per 100,000 inhabitants, as compared to Thailand and Sri Lanka, which had 1,108 and 4,085 emigrants, respectively, per 100,000 inhabitants.

affected by the tsunami. Unfortunately, it remains difficult to find such a candidate using the WDI data.

Another possibility is to average a larger set of countries not affected by the tsunami and to compare their trends in remittances before and after the shock. However, the difficulty with this approach lies in the selection of relevant countries and also in finding the appropriate weighting of the selected countries. For the sake of illustration, we compare in Figure 3 the remittance trends obtained for Indonesia and for a weighted average of the following countries using a uniform weighting scheme: Japan, Papua New Guinea, Malaysia, Australia, China, Republic of Korea, Laos, the Solomon Islands and New Zealand. While these countries have clearly very different economic conditions and development levels, we select them because the average share of remittances to GDP for these countries did not differ from that of Indonesia before the tsunami occurred (0.62% in both cases).[10]

Figure 3 shows a huge gap in Indonesia the year just after the shock, relative to the countries mentioned above, despite a similar trend before 2005. In particular, while the share of remittances in GDP has strongly increased in Indonesia between 2004 and 2005 (from 0.73% to 1.90%), the opposite pattern is found for the selected countries, with a fall of approximately 0.2 percentage points. From 2006 to 2011, the share of remittances remains rather constant in the other countries, while the decline in remittances in Indonesia suggests a progressive convergence to the level of remittances found in our selected countries. While these preliminary descriptive findings suggest that the tsunami had an immediate enhancing effect on the receipt of remittances in Indonesia, which then faded gradually with time, they nonetheless have to be interpreted with caution.

Insert Figure 3

Indeed, the control group that was selected to understand the comparative trend in remittances in Indonesia relative to other countries has no rigorous foundation. For instance, we could have selected other combinations of countries leading to the same average share of remittances before the tsunami. Additionally, Figure 3 shows that the situation between Indonesia and the control group was different from 1995 until 2000. Although this does not really seem plausible given the large gap in 2005, it could be that these differences during the pre-tsunami period had some influence on the receipt of remittances after the disaster. Next, we turn to the synthetic control approach in an attempt to assess the causal effect of the Indonesian tsunami on remittances.

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[10] A two-sample t-test leads to the rejection of the assumption that the average share of remittances to GDP differs between Indonesia and the other countries, with the critical probability being 0.982.

3. The synthetic control estimator

To estimate the causal effect of the 2004 tsunami on migrant remittances received in Indonesia, we face the classical problems in the evaluation program literature. The counterfactual situation corresponding to remittances in Indonesia had the tsunami not occurred cannot be observed. Because we use aggregate data at the country level, we decide to rely on the synthetic control approach, which was originally proposed in Abadie and Gardeazabal (2003) and further investigated in Abadie et al. (2010; 2014). Considering a set of potential countries that were not affected by the tsunami, this estimator will give a set of weights for these control units to form a synthetic control country. The latter has to mimic as best as possible a set of characteristics of Indonesia before the occurrence of the tsunami.

For this presentation, we consider a balanced longitudinal dataset of $J + 1$ units (countries in our case) observed over T years. Only the first unit is subject to a shock (the tsunami) that occurs at time T_0, with $T_0 < T$. It will be referred as the treated unit. We index the other units by j with $j = 2, \ldots, J + 1$. These J units, which are not affected by the shock, form the "donor pool" of potential comparison units. The numbers of pre-intervention and post-intervention periods, denoted by T_0 and T_1, respectively, are positive such that $T = T_0 + T_1$. In our setting, we have $T_0 = 10$ and $T_1 = 7$. Let X_1 be a column vector of pre-intervention characteristics of the treated unit, while X_0 is a matrix with J columns having similar interpretation for the potential control units.

In the synthetic control approach, the pre-intervention characteristics of the treated unit will be approximated by a linear combination of the control units in the donor pool. Let W be a column vector of weights to be calculated such that $W = (w_2, \ldots, w_{J+1})'$ with $0 \leq w_j \leq 1$ and $w_2 + \cdots + w_{J+1} = 1$. Each scalar corresponds to the endogenous weight of the unit j in the synthetic control to which the treated unit will be compared. The vector of weights W is chosen such that the synthetic unit will mimic as best as possible the treated unit before the shock (Abadie and Gardeazabal, 2003; Abadie et al., 2010). Because the difference in the pre-intervention characteristics between the treated and the synthetic control is $X_1 - X_0 W$, the endogenous weights W^* satisfy:

$$W^* = \min(X_1 - X_0 W)' * V * (X_1 - X_0 W) \tag{1}$$

subject to the constraints $0 \leq w_j \leq 1$ and $w_2 + \cdots + w_{J+1} = 1$. In (1), V is a positive definite and diagonal matrix whose elements indicate the relative importance of the selected covariates to measure the difference between the treated unit and the synthetic control $X_1 - X_0 W$. The set of endogenous weights W^* depends on V, and V will be chosen to minimize the mean squared prediction error of the outcome for the pre-intervention period.[11]

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[11] For more details, see the discussion in Abadie and Gardeazabal (2003, p. 128).

Next, the weights W^* are used to evaluate the consequences of the shock during the post-intervention period (from T_1 to T). Let Y_1 be a column vector indicating the values of the outcome of interest after the shock, while Y_0 is a matrix having a similar interpretation for the set of the J potential control units. The synthetic control estimator measuring the impact of the shock over the T_1 years is:

$$\Lambda = Y_1 - W^* * Y_0 \tag{2}$$

For each year of the post-intervention period, the synthetic control estimator Λ will correspond to the difference between the outcome observed for the treated unit and the outcome imputed for the synthetic control. As emphasized in Abadie et al. (2014), the difference between the synthetic control approach and a regression-based counterfactual of the outcome for the treated unit is that in the former case, the weights w_j used to construct a linear combination of the potential control units lies in the interval between zero and one, while these weights may be either negative or positive with the regression approach (and possibly greater than one).[12]

A concern with the definition of the synthetic counterfactual unit is the potential problem of unobserved heterogeneity that could impact the outcome under consideration. The solution proposed by Abadie et al. (2010) to account for unobserved factors requires matching on the pre-intervention values of the outcome. Assuming that there are enough periods of observation before the shock, the idea is that a synthetic control unit replicating the same trajectory as the treated unit is expected to be similar to the treated unit in both the observed and unobserved dimensions. After the shock, the difference in outcomes between the treated unit and the synthetic control will give the causal effect of the shock if the unobservables remain constant over the whole period.

A last comment is about inference. Because the synthetic control estimator measures the difference in outcome between the treated unit and the synthetic control unit, there is no standard error for the estimated gap, and bootstrapping would make no sense. To assess whether the results may be driven by chance only, Abadie et al. (2010) suggest running a set of placebo studies such that the synthetic control method is applied to the whole set of units that are part of the donor pool. Because these units were not affected by the shock by definition, then we should observe no change in the outcome just after the shock. This procedure will give a distribution of differences between each control unit and its corresponding synthetic control unit. Drawing on a statistical criterion, only those units for which the synthetic control method may reasonably mimic the fictitious treated unit before intervention will be kept.

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[12] While the regression estimator leads to some extrapolation that may potentially be outside the support of the data, the weights used in the regression approach still have a sum of one.

4. Results from the synthetic control estimator

In this section, we discuss the results obtained from the synthetic control estimator in Indonesia, the country most affected by the tsunami. As explained in the previous section, a preliminary requirement is to define the donor pool of potential control units, which is formed in our case by countries not having been affected by the tsunami. By definition, this excludes the four countries for which we want to investigate the consequences of the shock. Additionally, we restrict our sample to countries located in the Asian geographic zone. For some countries, we have no (or incomplete) information on remittances. Thus, in what follows, we focus on balanced panel data comprising Indonesia as treated unit along with the following 16 countries as our potential control group: Australia, Bangladesh, Cambodia, China, Fiji, Japan, Korea Rep., Laos, Malaysia, Nepal, New Zealand, Pakistan, Papua New Guinea, the Philippines, Samoa, and Vanuatu.

In Table 1, we show the share of remittances to GDP and log GDP per capita for the countries included in our synthetic group analysis. Not surprising, there are substantial differences by country concerning the share of remittances to GDP: 19.7% for Samoa, approximately 10% for the Philippines and Nepal, and less than 1% each for the countries of Japan, Australia, Papua New Guinea and Malaysia. During the period considered here, 1995-2011, Indonesia is ranked eighth as a remittance receiver by increasing order of importance. Because the synthetic control approach consists of averaging a set of endogenously chosen potential control units (with weights being in the [0;1] interval), countries with either a lower or higher share of remittances compared to Indonesia are needed. This condition is clearly verified in our sample. From 1995 to 2004 (before the shock), the average share of remittances is 0.618% in Indonesia, while lower values are found in five countries.

Insert Table 1

As explained before, the synthetic control country is a weighted linear combination of the 16 potential control units. We calculate the country-specific weights by considering the following list of predictor variables: lagged values of share of remittances to GDP, log of GDP per capita, log of population, and log of percentage of rural population. For these four covariates, we use year-specific values to mimic as best as possible the remittance trend observed during the pre-intervention period. In particular, we attempt to account for unobserved heterogeneity by introducing the lagged values of the remittance outcome. The mean squared prediction error (MSPE), which is the squared deviation between the outcome for the treated unit and the synthetic control unit, is minimized over the entire pre-tsunami period.

In the last column of Table 1, we show the set of weights defining the synthetic control units. According to our estimations, the synthetic control country that best mimics the remittance trend observed in Indonesia before the tsunami is a linear combination of Papua New Guinea

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(61.9%), Cambodia (16%), Japan (13.7%), Republic of Korea (5.1%) and Laos (3.2%). All of the other countries do not contribute to the definition of the synthetic Indonesia. Interestingly, we note that the largest endogenous weight is attributed to Papua New Guinea, which is the closest geographical neighbor of Indonesia. In Figure 4, we compare trends in remittances for Indonesia and the synthetic control unit. Overall, the synthetic control unit seemed to perform well before the tsunami, and there was very little difference between the share of remittances to GDP in Indonesia and in the synthetic control country between 1995 and 2004.[13]

Insert Figure 4

The situation looks very different immediately after the tsunami. As previously emphasized in our descriptive analysis, the share of remittances suddenly increased in Indonesia in 2005. However, we do not observe such a rise when considering the synthetic control unit for which the relative importance of remittances slightly decreased in 2005 compared to 2004. This is interesting, as the synthetic control unit was able to replicate very accurately the remittance trend observed in Indonesia until 2004.

Because the synthetic control country is an estimate of the counterfactual of what would have been observed in Indonesia in the absence of the shock, we conclude that the 1.35 additional points in share of remittances to GDP observed in 2005 in Indonesia (compared to the synthetic control group) could be interpreted as the causal impact of the tsunami. After 2005, we observe a continuous decline in the remittance gap between Indonesia and the synthetic unit: 1.08 points in 2006, 0.97 in 2007, 0.92 in 2008, 0.93 in 2009 (the year of the financial crisis), 0.68 in 2010, and 0.48 in 2011. Overall, the average difference calculated between 2005 and 2011 amounts to 0.91 points.

5. Robustness checks

A first way to check the validity of our results is to apply the following placebo exercise suggested in Abadie et al. (2010). Specifically, we assume that other countries were fictitiously affected by the natural disaster and check whether we see any break in the remittances behavior relative to its corresponding synthetic control group. In the upper part of Figure 5, we present the difference in the share of remittances to GDP for each country with respect to its own synthetic control unit. We exclude three countries for which we obtain an MSPE greater than 50.[14] In 2005, we find that the largest gap is observed for Indonesia. After the tsunami, the results from the placebo exercise show that Bangladesh experienced a larger increase in the share of remittances to GDP

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[13] During the 1995-2004 period, the average difference in the share of remittances to GDP between Indonesia and the synthetic unit is -0.002. The "worst" gap, which is observed in 1999, amounts to 0.11 point.

[14] The synthetic control approach performs very poorly in reproducing the pre-intervention trend in remittances for the three following countries: Nepal (MSPE=69.2), Vanuatu (MSPE=136.8) and Samoa (MSPE=230.2).

when compared to Indonesia. However, the highest increase in Bangladesh was not observed in 2005 but in 2006, 2007 and 2008, which makes the connection with the tsunami disaster less obvious.

Insert Figure 5

At the same time, we also note that for some countries, the gap with the synthetic unit is fairly substantial before the tsunami, sometimes around -1 or +1 percentage points (or even more in some cases). This suggests that for a few countries, the synthetic approach is not really successful in replicating the trend in remittances observed before the tsunami. Thus, we choose to exclude all countries for which we obtain an MSPE greater than 4. This criterion was satisfied by the following five countries (in addition to Indonesia by definition): Australia, China, the Republic of Korea, Malaysia and the Philippines. Our results shown in the lower part of Figure 5 leave little doubt as to the existence of a link between the tsunami and the increase in migrant remittances in Indonesia.

Among the six countries considered here, the profile observed in Indonesia is significantly different from the others. From 2005, remittances were lower on average in Australia, China and the Philippines compared to the corresponding synthetic control unit. While the synthetic unit mimics well the remittance trend observed for the Republic of Korea both before and after the tsunami, we note a small increase in the difference in share of remittances to GDP in Malaysia starting from 2005 until 2007, but with a lower intensity compared to Indonesia. Given the increasing trend in GDP over the period in that country, we conclude that the tsunami led to substantial remittances from migrants to support the local population.

Next, we provide some comparative evidence for the four countries that were the most affected by the disaster: Indonesia, Sri Lanka, Thailand and India.[15] According to our results shown in Figure 6, it seems that only Indonesia experienced a surge in remittances following the December 2004 tsunami, which was gradually reduced after 2005. In the other countries, the difference in the share of remittances to GDP over its corresponding synthetic control tended to be negative after 2005. For Thailand and India, we do not observe any break in 2005, with the differential being around -0.5 points, which extends a trend observed starting from 2004. For Sri Lanka, the profile is more contrasted. In 2005, compared to the synthetic control, the difference in the share of remittances to GDP increased by 0.75 percentage points compared to 2004, while the gap calculated for 2004 was much lower than in 2003 (-1.25 points).

Insert Figure 6

As a final step, we decide to compare the results obtained from different estimators when estimating the effect of the tsunami on remittances in Indonesia. In the literature on program evaluation, the classical approach is to use a difference-in-differences (DID) estimator. With panel

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[15] A specific synthetic control unit is calculated for each treated country, with the potential donor pool consisting of 16 countries. These additional results are available upon request.

data, this is a comparison of how the variable of interest has changed following the shock for treated and control units. A crucial assumption for the validity of the DID is the parallel trend assumption, which requires the trend in outcome to be equal for treated and control units before the shock. We investigate the relevance of this assumption using first our sample of 17 countries (including Indonesia).

The hypothesis of a parallel trend from 1995 to 2004 is clearly rejected by the data. For Indonesia, there was a sharp increase in 1998, and then the weight of migrant remittances appears relatively stable from 2000 to 2004. Conversely, for the 16 other countries not affected by the tsunami, the trend is of a strong increase from 1997 to 2001 before declining in 2002 and 2003. Thus, a DID approach applied to the full set of countries would lead to misleading estimates concerning the causal impact of the tsunami. As a consequence, we restrict our attention to the subset of countries involved in the definition of the synthetic control group: Papua New Guinea, Cambodia, Japan, the Republic of Korea, and Laos. Now, we find very similar trends in the share of remittances to GDP both for Indonesia and the control countries, which was expected because the synthetic control was determined endogenously to mimic as closely as possible the situation in Indonesia before the tsunami.[16]

Next, we apply the DID approach to this subsample. Let Y_{it} be the remittance outcome in country i at time t, X_{it} a set of explanatory variables, $\mathbb{1}_{it}$ a set of year-specific dummies, $\mathbb{1}_{t \geq 2005}$ a post-tsunami dummy and $Indonesia$ a dummy variable equal to one for Indonesia (and zero otherwise). We begin by estimating the following model using OLS:

$$Y_{it} = X_{it}\beta + \sum_t \delta_t \mathbb{1}_{it} + \lambda * Indonesia + \gamma * Indonesia * \mathbb{1}_{t \geq 2005} + \varepsilon_{it} \tag{3}$$

where ε_{it} is a random perturbation. In (3), the coefficient γ measures the causal effect of the tsunami on remittances. In a second specification, we introduce country fixed effects in the regression to account for the unobserved characteristics of the country that remain time invariant over the period:

$$Y_{it} = X_{it}\beta + \sum_t \delta_t \mathbb{1}_{it} + \lambda * Indonesia + \gamma * Indonesia * \mathbb{1}_{t \geq 2005} + \vartheta_i + \varepsilon_{it} \tag{4}$$

with ϑ_i a country-specific component[17]. Finally, we try to better account for treatment and outcome being correlated because of the presence of unobservables by estimating a linear factor model designed for longitudinal data. Specifically, we estimate the interactive fixed effect model recently proposed by Bai (2009), which accounts for some interaction between factors varying over time and heterogeneous specific-unit terms called factor loadings:

$$Y_{it} = X_{it}\beta + \sum_t \delta_t \mathbb{1}_{it} + \lambda * Indonesia + \gamma * Indonesia * \mathbb{1}_{t \geq 2005} + \vartheta_i + \kappa_i' * f_t + \varepsilon_{it} \tag{5}$$

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[16] These additional results are available upon request.
[17] We do not include the country-specific linear time trend in our regression because some covariates also evolve in a linear way.

where κ_i is a vector of factor loadings of dimension $(r * 1)$ and f_t is a vector of common factors of dimension $(r * 1)$ such that $\kappa_i' * f_t = \kappa_{i1} f_{1t} + \cdots + \kappa_{ir} f_{rt}$.[18] Given the small number of countries in our data, we estimate the interactive model with either one or two factors. Our various estimates are shown in Table 2.

In column (1), we present the OLS results corresponding to equation (3). We find that the interaction term crossing the Indonesian dummy and the post-tsunami period is significant at the 1% level. This means that compared to the other countries under consideration, the contribution of remittances to GDP has on average increased by 0.97 additional percentage points each year in Indonesia. Interestingly, we find very similar results when controlling either for country unobserved heterogeneity using a fixed effect regression (column 2) or for more complex forms of unobserved heterogeneity using the interactive fixed effect model (columns 3 and 4). Comparative evidence among the fixed effect DID, interactive fixed effect DID and synthetic control estimators is illustrated in Figure 7. Whatever the estimator we consider, our empirical results highlight the existence of a peak in remittances received in Indonesia just after the 2004 tsunami, which gradually fades with time.

Insert Figure 7

6. Conclusion

In this paper, we have examined the impact of the 2004 Indian tsunami on international remittance transfers using aggregate country data and the synthetic control methodology (Abadie et al. (2010; 2014). Our treatment country is Indonesia, the hardest hit country in terms of causalities, homeless people and the economy. The synthetic control methodology implies identifying the causal impact of the disaster by comparing the share of remittances to GDP in Indonesia with a counterfactual group constructed by using the synthetic controls of countries that were not affected by the tsunami but that had a very similar pre-shock trend in international remittance flows.

Our main results are twofold. First, we determined that there was a large impact on remittances in Indonesia just after the tsunami, with 1.35 additional points in share of remittances to GDP observed in 2005 (compared to the synthetic control group). Second, the gap in remittances observed between Indonesia and the synthetic control decreased steadily over the succeeding years and amounted to 0.5 percentage points at the end of the period (2011). We assess the validity of our results employing different robustness checks and utilizing a difference-in-difference approach with various forms of unobserved heterogeneity. Overall, our results find that the synthetic control

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[18] As emphasized in Bai (2009), the multiple interactive model includes the usual additive fixed effect specification as a special case. Estimation of the interactive fixed effect model is discussed in section 8 of Bai (2009, p. 1252-1256).

approach is a powerful tool to assess the consequence of a natural disaster when only aggregate data are available to researchers.

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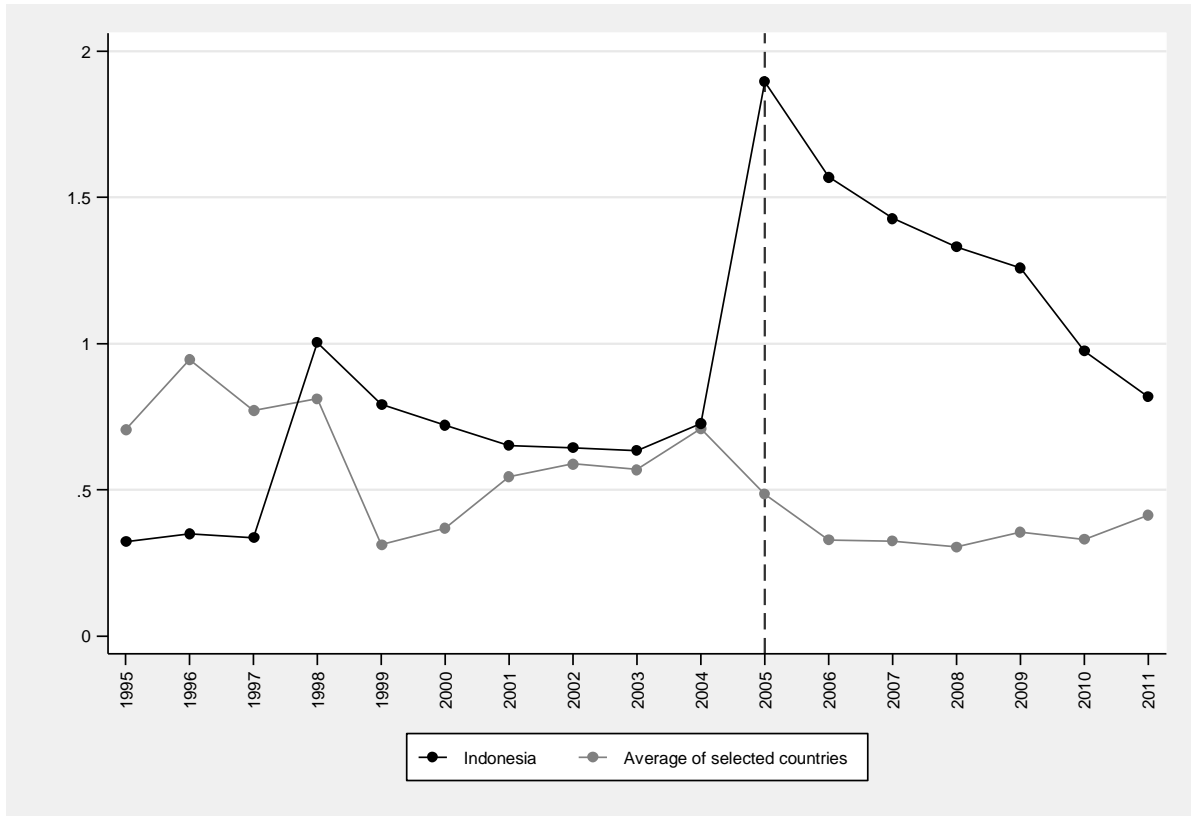
Figure 1. Trends in remittances 1995-2011
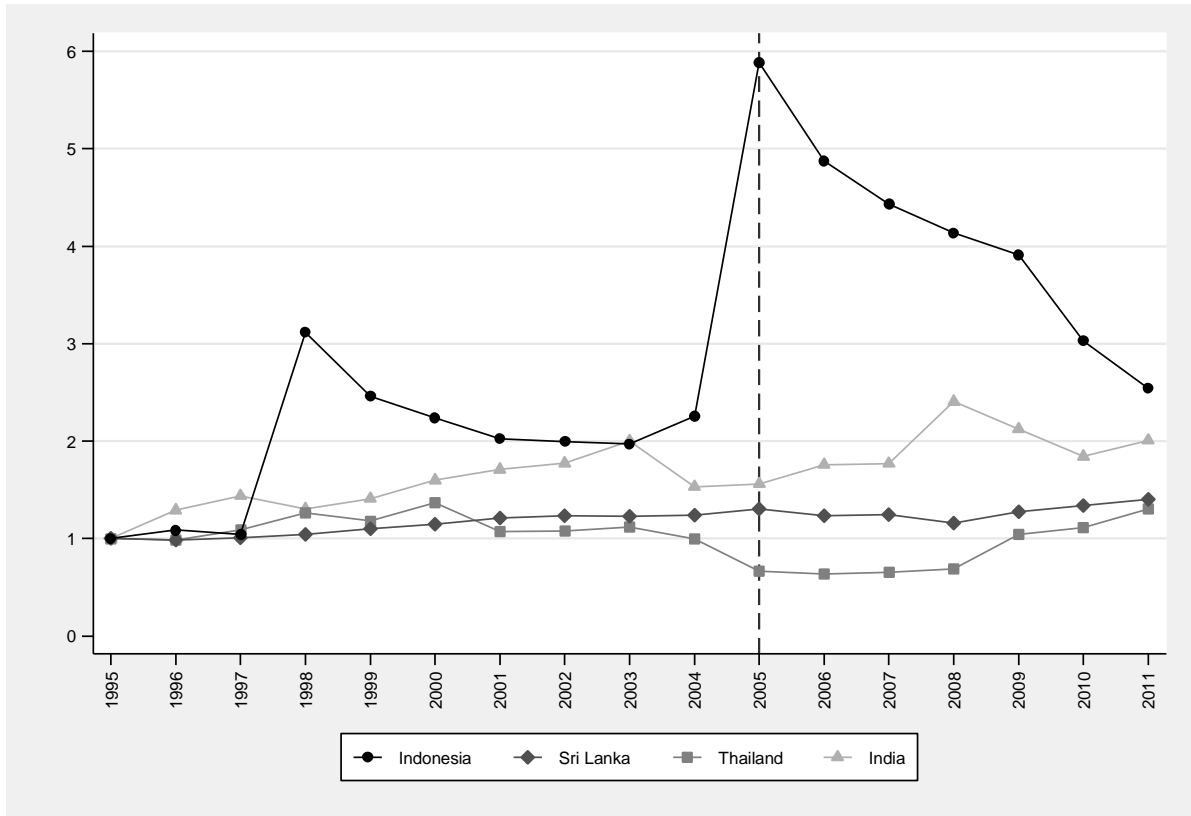
Source: WDI 2013, authors' calculations.

Figure 2. Trends in GDP 1995-2011
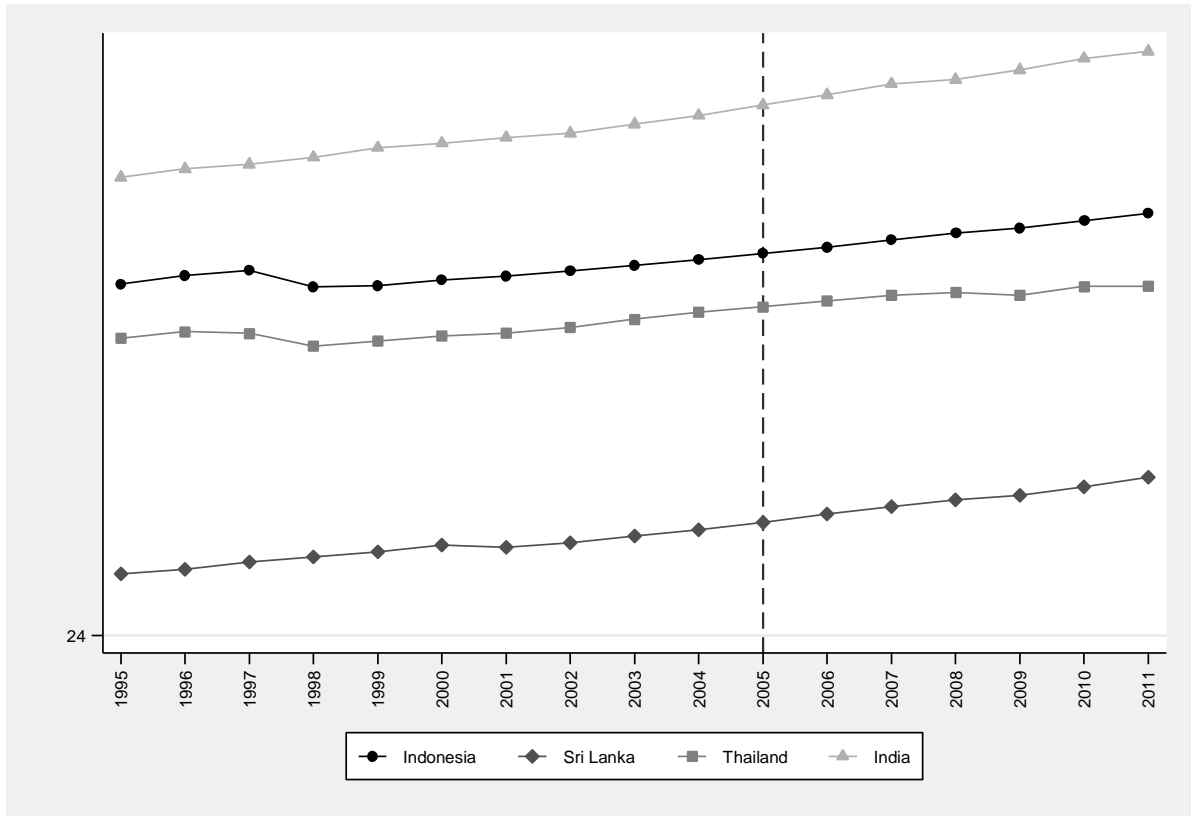
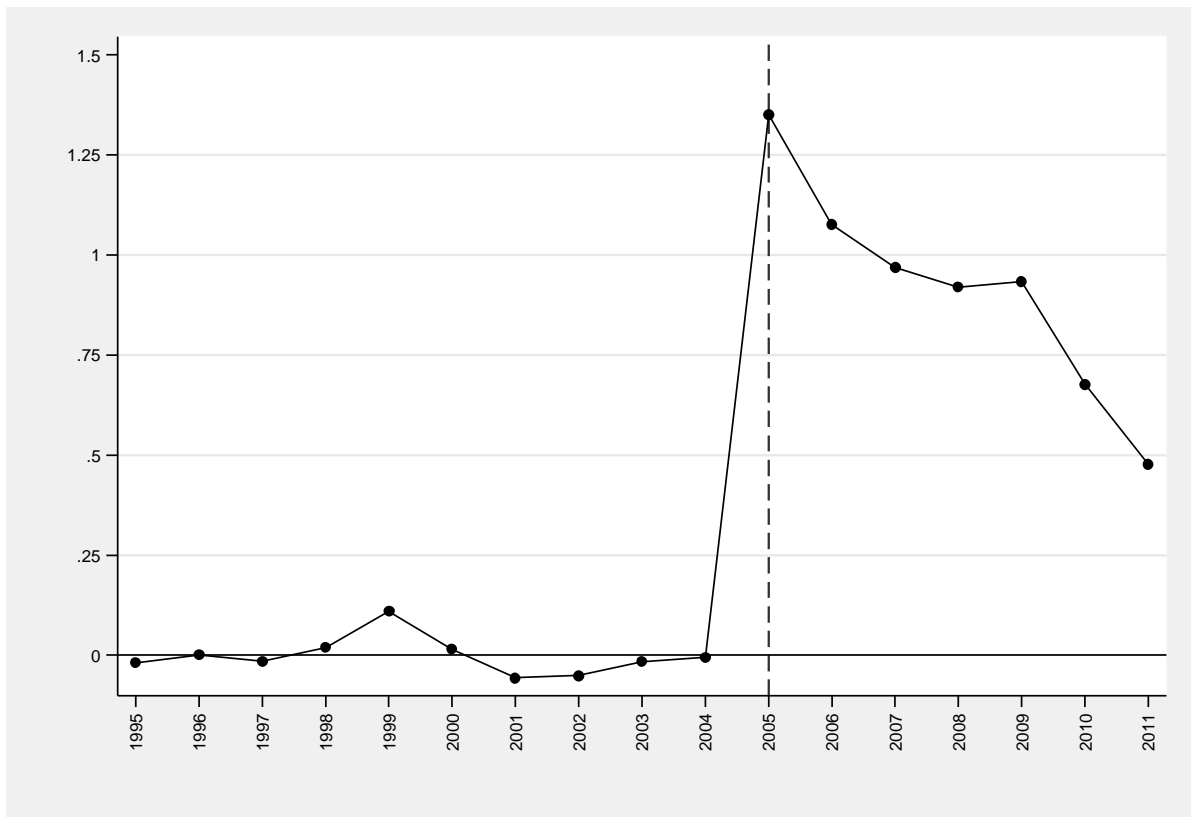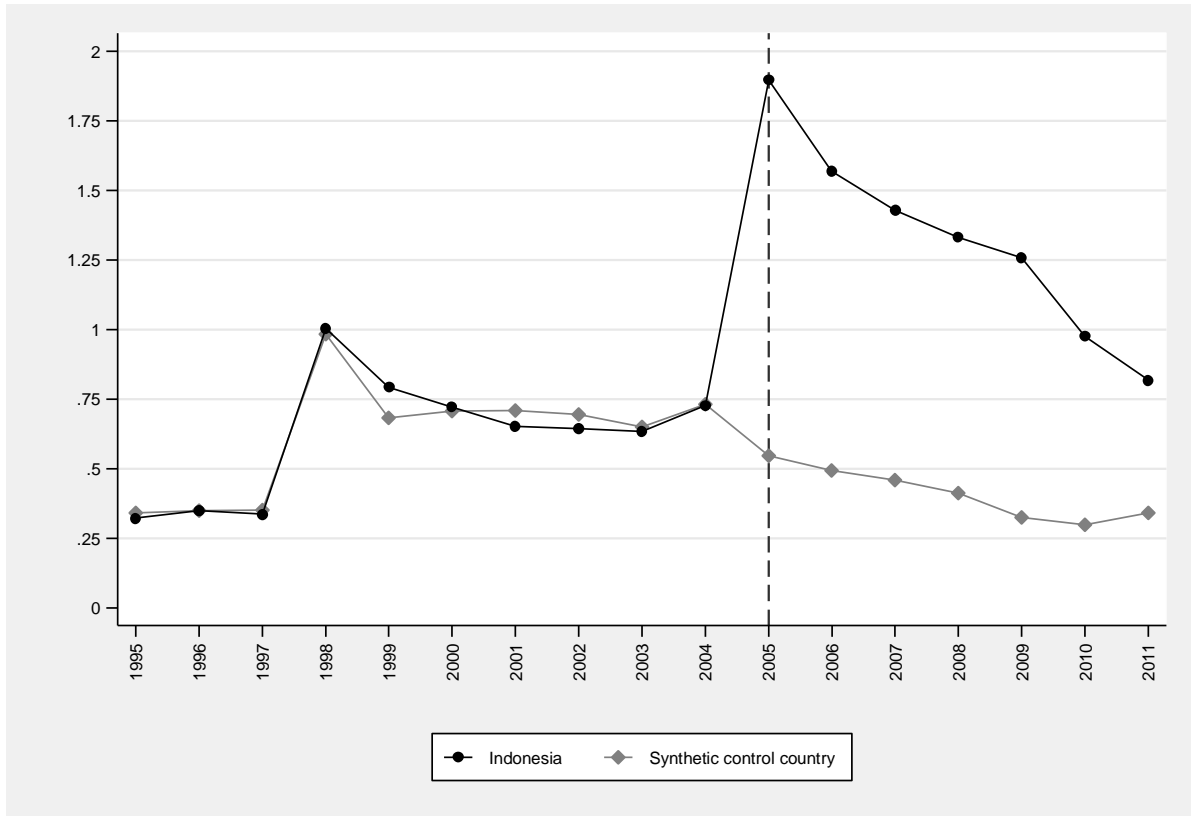Source: WDI 2013, authors' calculations.

Figure 3. Trends in remittances 1995-2011: Indonesia versus selected countries

Source: WDI 2013, authors' calculations.
Note: selected countries are Japan, Papua New Guinea, Malaysia, Australia, China, Republic of Korea, Lao PDR, Solomon Island and New Zealand.
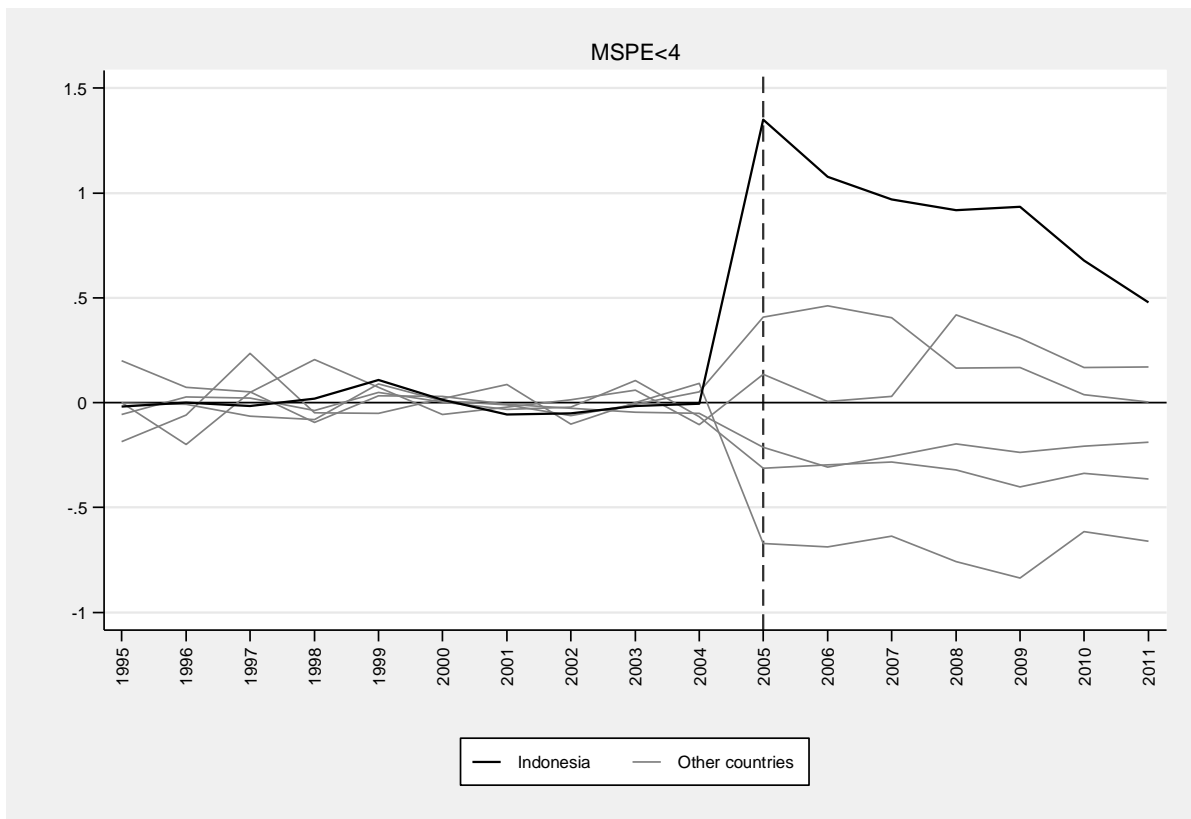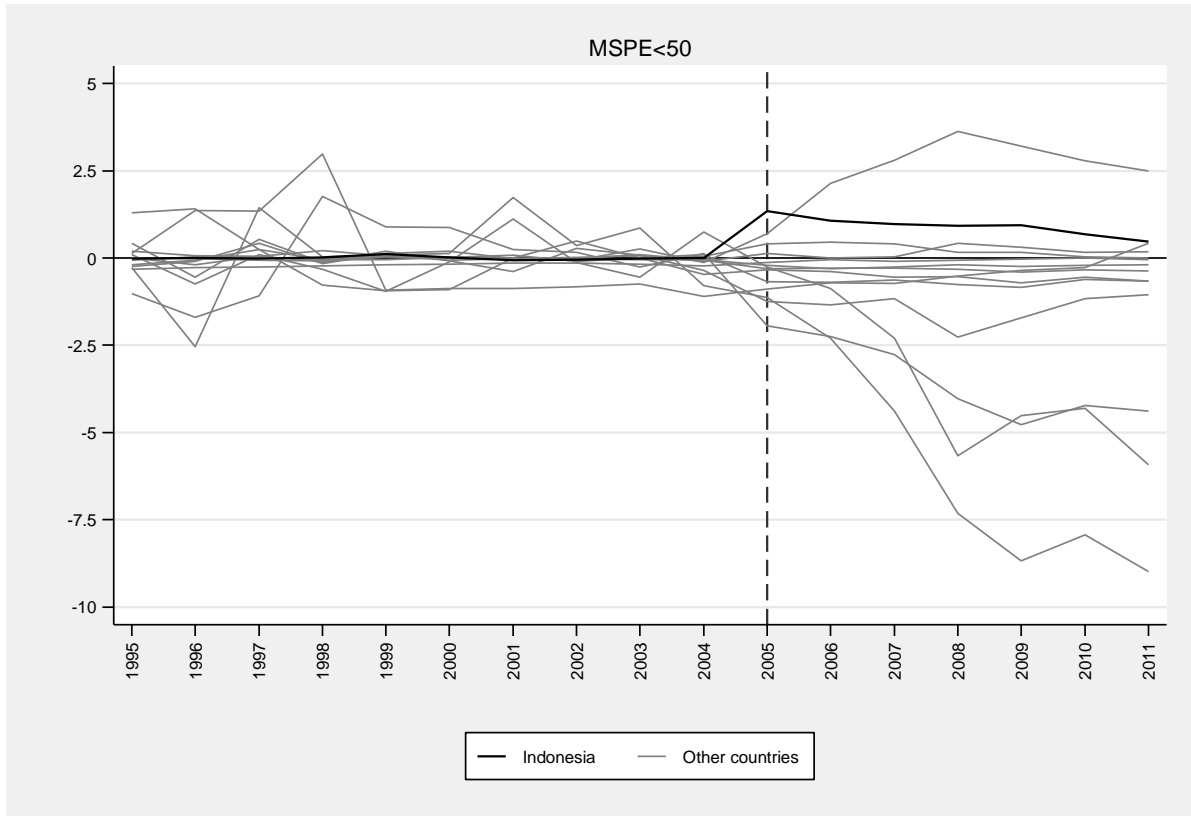
Figure 4. Trends in remittances: Indonesia vs. the synthetic control

Source: WDI 2013, authors' calculations.

Note: the synthetic control country is determined using year-specific values for share of remittances to GDP, log of GDP per capita, log of population and log of percentage of rural population as predictor variables.

Figure 5. Trends in remittances: Indonesia versus synthetic control country, placebo study

MSPE<50

MSPE<4

Source: WDI 2013, authors' calculations.
Note: the synthetic control country is determined using year-specific values for share of remittances to GDP, log of GDP per capita, log of population and log of percentage of rural population as predictor variables.
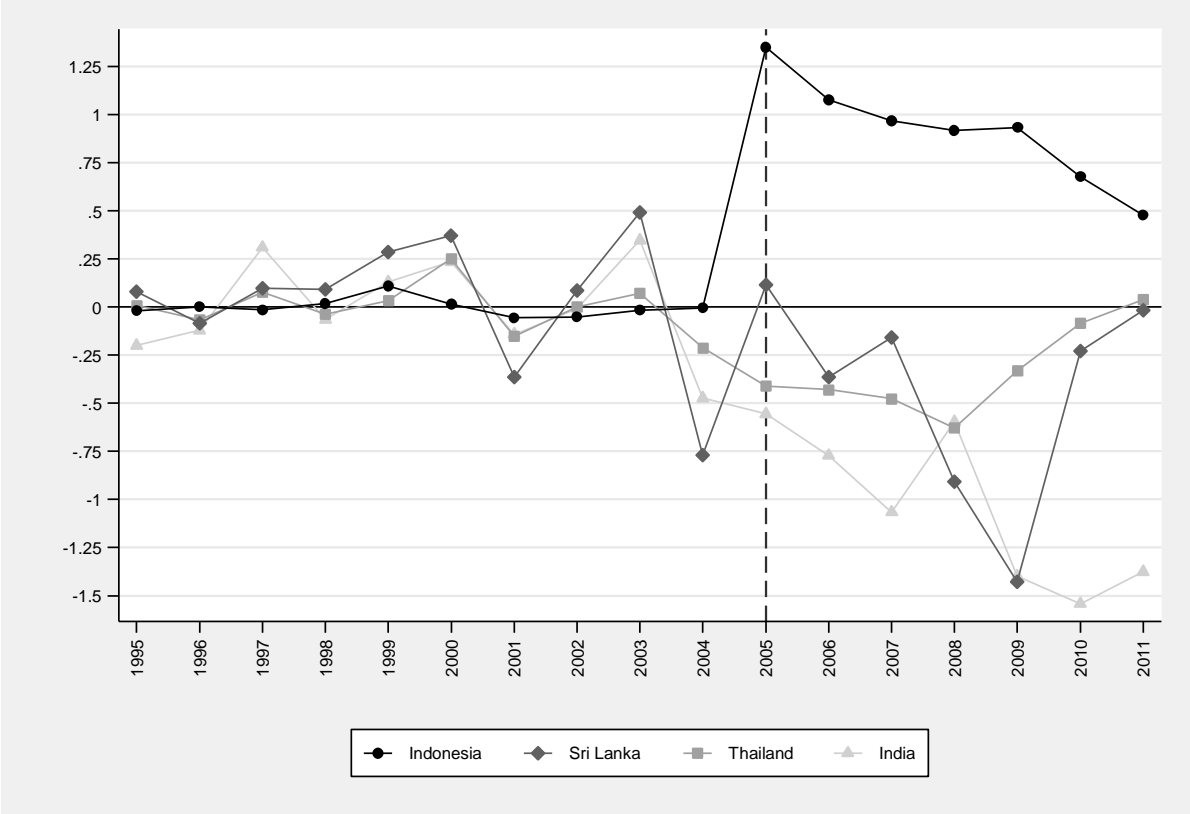
Figure 6. Trends in remittances: Indonesia, Sri Lanka, Thailand and India versus synthetic control country

Source: WDI 2013, authors' calculations.

Note: the synthetic control country is determined using year-specific values for share of remittances to GDP, log of GDP per capita, log of population and log of percentage of rural population as predictor variables.
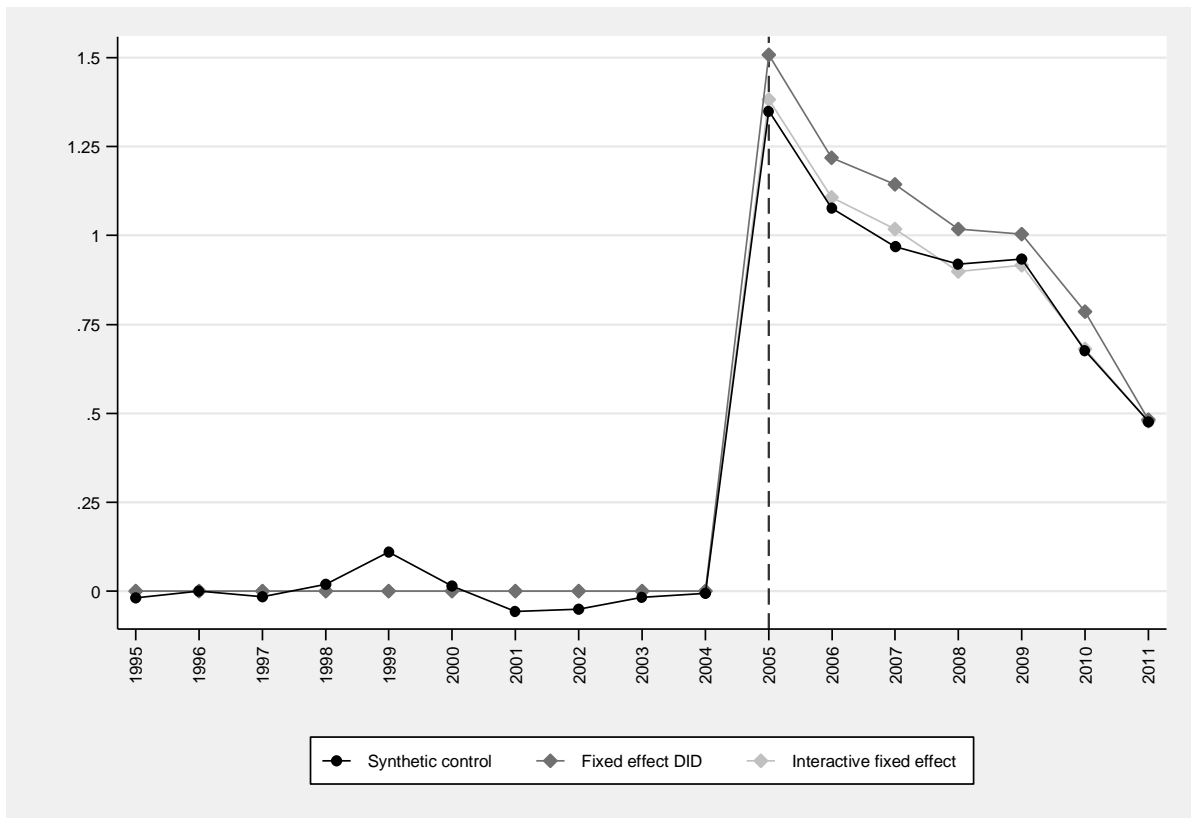
Figure 7. Trends in remittances: comparative evidence for Indonesia using different estimators (fixed effect DID, interactive fixed effect DID, synthetic control)

Source: WDI 2013, authors' calculations.

Note: the synthetic control country is determined using year-specific values for share of remittances to GDP, log of GDP per capita, log of population and log of percentage of rural population as predictor variables. The same controls are used when estimating the fixed effect difference-in-differences and interactive fixed effect (with two factors) estimators.

Table 1. Characterization of the synthetic control country for Indonesia

Country	Share of remittances to GDP (average)			Log GDP per capita (average)	Weight in the synthetic control
	Before tsunami	After tsunami	1995-2011		
Australia	0.478	0.142	0.340	10.333	0.000
Bangladesh	4.482	10.013	6.760	6.985	0.000
Cambodia	2.405	1.867	2.183	7.167	0.160
China	0.502	0.483	0.494	8.181	0.000
Fiji	3.249	5.484	4.169	8.306	0.000
Japan	0.030	0.030	0.030	10.297	0.137
Korea, Rep.	0.957	0.763	0.877	9.948	0.051
Lao PDR	1.015	0.456	0.785	7.355	0.032
Malaysia	0.351	0.631	0.466	9.350	0.000
Nepal	4.550	19.527	10.717	6.911	0.000
New Zealand	1.403	0.560	1.056	10.067	0.000
Pakistan	2.823	4.729	3.608	7.619	0.000
Papua New Guinea	0.242	0.088	0.179	7.619	0.619
Philippines	9.339	11.420	10.196	7.986	0.000
Samoa	18.889	20.835	19.690	8.130	0.000
Vanuatu	8.164	1.612	5.466	8.216	0.000
Indonesia	0.618	1.325	0.909	8.039	

Source: WDI 2013, authors' calculations.

Table 2. Characterization of the synthetic control country for Indonesia

Variables	(1)	(2)	(3)	(4)	(5)
	OLS	Fixed effects	Interactive	Interactive	Synthetic
Indonesia	-2.496***				
	(0.764)				
Indonesia x After tsunami	0.969***	1.023***	0.850***	0.919***	0.915
	(0.227)	(0.180)	(0.235)	(0.054)	
Explanatory variables	YES	YES	YES	YES	
Time fixed effects	YES	YES	YES	YES	
Country fixed effects	NO	YES	YES	YES	
Number of factors			1	2	
Number of observations	102	102	102	102	102
R²	0.399	0.629			

Source: WDI 2013, authors' calculations.
Note: robust standard errors are in parentheses, significance levels being 1% (***), 5% (**) and 10% (*). The list of control variables includes log of GDP per capita, log of population and log of proportion of rural population. In addition to Indonesia, the subset of countries comprises Papua New Guinea, Cambodia, Japan, Republic of Korea and Lao PDR. These countries form the synthetic Indonesia unit.