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Does Aid Promote or Hinder Industrial Development?

Quake Lessons from China

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Abstract: We adopt a disaggregate approach to contribute to the literature on the effectiveness of aid. Specifically, we examine whether post-disaster aid provided to a subsample of Chinese counties affected by a devastating earthquake in 2008 affects the sectoral composition of local economies. Consistent with the Dutch disease hypothesis we find that counties receiving (more) aid – even “nearby counties” not damaged by the earthquake – tend to suffer from a contraction of the manufacturing sector. This effect can be measured in terms of income earned and employment. Innovative features of the paper include its regional perspective; its identification strategy (which rests on a special provision in Chinese policy—pairwise aid provision); and its focus on Dutch disease effects in the context of post-disaster aid.

Keywords: Aid; Industrial Development; Manufacturing; Dutch disease, Natural disasters

JEL codes: O23; O14

1. Introduction

The literature on the economic impacts of aid does not produce robust evidence of either positive or negative effects, and the effect of foreign aid inflows on economic growth of poor countries remains disputed. Why does aid fail to produce robust growth effects? Some analysts have proposed that aid, and other economic windfalls, may adversely affect the quality of governance and institutions in receiving countries (e.g., Bräutigam and Knack 2004, Dalgaard and Olsson 2008).[1] Others emphasize more conventional, economic mechanisms, such as the well-known Dutch Disease to explain the mixed performance of aid (e.g., Rajan and Subramanian 2011).

Estimating the growth effect of aid is complicated by two types of 'heterogeneity.' First, the economic effects of aid may vary across countries, depending on local conditions (institutions, policies, geophysical factors). Second, most models explaining growth are based on aggregate aid data, but not all forms of aid are expected to have an economic impact in the short term (Clemens et al. 2012). Because of these two reasons, and because of persistent concerns about the potential endogeneity of aid variables in growth models, it may be unclear what is really captured by the 'average treatment effect of aid' as estimated in regression models explaining growth.

In an effort to further advance our understanding of the economic effects of aid, we adopt a "disaggregate" perspective, and focus on the impacts of a specific form of aid in a specific country. We consider post-disaster reconstruction aid, following a devastating earthquake, in Sichuan Province, China, in 2008. Our perspective allows for relatively clean

[1] Windfall gains may undermine accountability of politicians (Paler 2012). Political scientists hypothesize that the origins of revenues determine how public funds are spent. It is often believed that taxation causes good governance by engaging citizens, motivating them to demand more from their leaders. Taxation induces the participation of citizens in political processes because it creates a sense of "ownership of public resources," and because information asymmetries between leaders and citizens are likely smaller when public revenues derive from taxes. See also the work of Robinson et al. (2006). Caselli and Michaels (2013), and Djankov et al. (2008).

assessment of the economic consequences of this type of aid, and in particular enables us to probe the relevance of Dutch disease arguments to explain the failure of aid to foster growth. Moreover, the magnitude of domestic aid flows to affected counties was predominantly exogenous, for reasons discussed in detail below, which enables us to interpret the post-disaster aid allocation as a 'natural experiment.'

In addition to speaking to the literature on the economic effects of aid inflows (or windfall gains more broadly), we hope this paper contributes to the literature on the economics of disasters and post-disaster recovery. While some economists may argue that the aid literature has ballooned beyond appropriate proportions, the economic literature on disasters and post-disaster recovery is surprisingly (or distressingly) modest—especially in light of the first-order economic consequences of natural disasters for the lives and well-being of millions of people (see also Hirshleifer, 1987).

Three small strands of literature explore the consequences of disasters. Various papers have adopted a micro perspective, and explore adaptation, mitigation, and coping strategies of individual households in response to (the threat of) shocks (e.g., Townsend 1994, Udry 1994). Another strand consists of case studies of specific disasters and the economic responses that eventuated (e.g., Halliday 2006, van den Berg 2010). Finally, following pioneering work of Albala-Bertrand (1993), a handful of papers probes the economic consequences of disasters in a cross-country framework. To some extent this latter strand contains parallels with dominant approaches in the aid literature in terms of its focus and methodology. Skidmore and Toya (2002) explain long-term effects of disasters, focusing on average growth, capital accumulation and total factor productivity over a 30 year period. Noy (2009) explores short-term macro-economic consequences of disasters, and seeks to explain variation in the associated damages. He finds a significant average effect on various macroeconomic variables, but also documents that consequences are country-specific as countries differ in their (institutional) ability to cope. Further disaggregation yields further insights, and Loayza et al. (2012) conclude “different disasters affect growth in different economic sectors differently.”

The literatures on aid and disasters are naturally linked as disaster-struck countries or regions are more likely to qualify for additional aid inflows. These linkages may be multi-faceted and potentially complex. For example, Raschky and Schwindt (2009) propose that the Samaritan’s dilemma may be relevant in the domain of disasters and aid—aid may crowd out protective measures, inviting larger damages.[2] We know surprisingly little about the impact of such aid flows. Noy (2009, p.229) argues “the impact of aid surges that oftentimes follow disasters are also worth exploring. Aid surges are a topic of an active research agenda, but no paper that we are aware of places these within the context of post-disaster recovery. Yet, in a cross-country framework, even the direction of aid flows following disasters appears to be difficult to pin down…”

The main objective of this paper is to analyse the economic consequences of post-earthquake aid flows in rural China, and in particular to explore whether aid may inadvertently contribute to a shrinking manufacturing sector because of Dutch disease effects. That is, we analyse whether aid flows are associated with a declining share of manufacturing in the size of the economy (as a reduced form model) and, if so, also explore whether changes in the relative price of non-traded goods are the linking pin—the Dutch disease transmission channel.

The term “Dutch disease” describes a contraction of the traded or manufacturing sector, following an appreciation of the real exchange rate (a rise in the relative price of non-traded goods). The theory behind Dutch disease phenomena is simple. First, aid inflows may

[2] This is an additional reason why models based on the intensity of disaster (measured in terms of damages or casualties) instead of the occurrence of disasters need to worry about the potential endogeneity of disasters in their regression models.

disproportionally target the non-tradable sector (e.g., think of post-disaster reconstruction efforts), increasing wages in that sector, thereby drawing (skilled) labour into that sector. This process will bid up wages more generally, and as a consequence reduce profitability in manufacturing (as the prices of their output – traded goods – are fixed). This is the so-called resource movement effect (Corden and Neary 1982).[3] Second, higher wages imply a boost to local income, which will (further) shift up demand for non-traded goods. This is the spending effect. To restore equilibrium on the labour market, labour should flow from a shrinking manufacturing sector to expanding non-traded sectors, and the increase in consumption of traded goods is due to extra imports financed by the inflow of aid.[4] For a recent summary of Dutch disease effects due to natural resource windfalls, see Van der Ploeg (2011).[5]

Various studies provide empirical support for the existence of a shrinking manufacturing sector in the presence of windfall gains. In the context of natural resource windfalls, for example, refer to Ismail (2010) and Brahmbhatt et al. (2010). In the context of aid flows, Rajan and Subramanian (2011) develop a convincing story based on a within-country, cross-industry model. They demonstrate that aid negatively affects growth of the manufacturing sector, and identify a rise in the price of non-traded goods relative to traded goods as the transmission mechanism.

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[3] A variant hereof explains why disasters can have Dutch disease effects even in the absence of aid inflows. Hallegatte and Ghil (2008) observe that the timing of disasters, relative to the phase of the business cycle matters a great deal for the eventual economic impact. When the economy is depressed, damages are lower (because recovery efforts will active unused resources, and there are unsold inventories to tap into). Disasters during high-growth phases bid up wages and causes wage inflation (undermining profitability of manufacturing).

[4] In the longer term, when capital is also mobile across sectors, possibly shifting from the traded to the non-traded sector as well, then the productivity and supply of non-traded goods may change. Wage-rental ratios will adjust and a new equilibrium ensues, depending on the labour intensity of the non-traded versus the traded sector. In the medium-term, therefore, the overall impact on competitiveness of the manufacturing sector is ambiguous (see also Torvik 2001).

[5] A similar framework may be used to analyse the consequences of demand shocks (e.g. Moretti (2010). For example, Aragon and Rud (2013) study the consequences of a local demand shock caused by a large mining firm that started procuring a larger fraction of its inputs locally. Their main finding is that such a demand shock raised (nominal and real) incomes and prices of non-tradables in nearby communities. This effect declines monotonically with distance from the region where inputs are purchased.

Why should economists care about whether the manufacturing sector shrinks or expands, if the dynamics of sectoral composition reflect market forces and evolving comparative advantages? Several arguments have been proposed in the literature, building on the idea that manufacturing is the long-term engine of growth for economies. Jones and Olken (2005) argue that the traded goods sector is the main channel via which local economies absorb best technologies or management practices from abroad. Others have argued that manufacturing exhibits increasing returns to scale at the sector level (i.e., beyond individual firms), for example via human capital spill-overs or "learning-by-doing" processes (Matsuyama 1992, Van Wijnbergen 1984, Krugman 1987, Sachs and Warner 1995). According to these perspectives, a shrinking manufacturing sector casts an economy to a slower growth path with detrimental long-term consequences.[6] Possibly offsetting these effects, Adam and Bevan (2006) argue that the inflow of aid may also have positive supply-side impacts in the form of aid-financed public expenditures which may generate intertemporal productivity spill-overs (e.g., infrastructure).

Our paper is innovative because it contributes a regional perspective to the literature on the disaster-aid nexus. Rather than adopting a household or cross-country perspective, we are the first to analyse the economic consequences of post-disaster aid on economic performance at the regional level. We are also the first to analyse whether post-disaster aid generates Dutch disease effects. This implies probing the robustness of the results on aid more generally, as reported by Rajan and Subramanian (2011), in a different context—focusing on China and on one specific form of aid (following the 2008 earthquake in Sichuan). We also have an innovative identification strategy, due to a unique provision in the Chinese policy response to the earthquake. Specifically, affected counties were matched to

[6] Matsen and Torvik (2005) analyse optimally managed Dutch disease effects in the context of considerable resource wealth—balancing the positive effects of resource extraction with the productivity losses in manufacturing.

unaffected provinces based on the degree of loss in recipient counties and income level (GDP) of donor provinces, and selected provinces were forced to contribute at least 1% of their budget revenue as domestic aid to promote post-disaster recovery. Because the decision was made rather quickly, prior to full knowledge about the true magnitude of economic losses, and fiscal revenue of "matched provinces" varies greatly, the inflow of aid at the county level displays considerable (exogenous) variation, as will be shown. We will also discuss, and deal with, various challenges to our identification strategy.

This paper is organised as follows. In section 2 we describe the background to our analysis. We describe the (consequences of the) earthquake, and the unconventional policy response it triggered. We try to develop the argument that the Chinese policy response created a distribution of aid flows that may be best characterised as a natural experiment in aid provision. In section 3 we describe our data and the details of our identification strategy. Section 4 presents both the reduced form results, highlighting that aid crowds out manufacturing, as well as suggestive evidence regarding the transmission channel—changes in the relative prices of non-traded goods and services. Our conclusions ensue in section 5.

2. Background

On May 12, 2008, a large earthquake hit *Wenchuan*, a relatively poor and rural area in Sichuan province (in China). It killed at least 69,000 people, and left between 4.8 and 11 million people homeless. According to one estimate, the total economic loss reached 845 billion *yuan* (or 121 billion USD) (FAO 2008, COHD 2009).[7] Complicating post-disaster recovery, the local infrastructure—roads, but also government buildings and so on—was badly damaged in many localities.

[7] The exchange rate at the time of the earthquake was about 1 US dollar = 7 yuan.

China is a hierarchical society with a top-down governance structure (Zhang, 2006). In the event of an earthquake, this governance structure faces various challenges in effectively delivering the massive amount of aid that is required to rebuild disaster areas. With many government buildings damaged, or many casualties among lower-tier civil servants, rebuilding local government capacity may be a daunting yet necessary task for the government to effectively respond to the crisis. In addition, widespread information asymmetries between different levels of government implies upper-level government cannot quickly obtain accurate information about the extent of local damages (which varies a lot), or the required resources for recovery. Consequently, the traditional top-down aid strategy cannot respond speedily and effectively to heterogeneous local needs.

After the earthquake, the central government immediately tried to ship tents and other relief supplies by train and road to Chengdu, the capital city of Sichuan Province. However, the massive inflow of supplies in such a short time caused a glut in the transportation system, greatly delaying shipments to disaster areas. In response, the Chinese government sought a decentralised solution and devised an innovative pair-wise province-to-county aid strategy. [8] This strategy worked as follows. Affected counties in the earthquake region were paired with unaffected provinces, usually in the more developed coastal region. The paired province took responsibility for providing aid for the recovery and reconstruction in its designated county. Specifically, the 18 worst affected counties were paired with the 18 richest provinces. Selected provinces were obliged to transfer 1% of their revenue to their matched county, for three consecutive years (2008-2010). Much of the aid was invested in projects to rehabilitate local infrastructure. In addition, one high-level official from each donor province was sent to its disaster county to lead the aid effort. This institutional innovation introduced yardstick competition into the process of disaster relief and recovery. Provincial governments in the

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[8] "The General Office of State Council's notice about pairwise aid policy to support the disaster areas' reconstruction after the *Wenchuan* earthquake." (2008, No.53) issued by the General Office of State Council of China, 11th June, 2008.

coastal region were evaluated based on their performance in terms of recovery and reconstruction in their assigned county. This pairwise aid strategy was regarded a great success as the reconstruction effort finished on time (i.e., within a three year period). [9] However, despite anecdotal evidence and numerous media reports on this governance innovation, empirical studies to evaluate this new practice are lacking. Here we seek to analyse the effect of varying the inflow of decentralised aid on industrial development.

In addition to the 18 “paired disaster counties” that qualified for support from a wealthy province, another 15 counties were damaged by the earthquake but were not selected for matching because the initial assessment (perhaps incorrectly) suggested that local damages were less severe. These so-called “non-paired disaster counties”—as well as the ‘paired’ ones—qualified for a uniform support package provided by the central government.[10] Most of the fund was disbursed by the Ministry of Civil Affairs. We examine the consequences of aid received by both paired and non-paired disaster counties on local economic structure by using the non-disaster counties which do not border any of the paired disaster counties as a sample of controls in a differences-in-difference (DID) analysis (such counties will be called “other non-disaster counties”). To address whether the effects we document are due to the inflow of aid, and not to direct damages of the earthquake (see the paragraph summarizing challenges to identification in section 3), we also distinguish between 9 non-disaster counties that are the neighbor of a paired disaster county (picking up any contagion or spill-over effects associated with an inflow of aid) and 96 so-called “other non-disaster counties” that did not suffer from the earthquake, nor from any aid-induced spill-over effects.

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[9] With apparent success of this strategy, the Chinese government has now adopted a similar strategy in developing the western regions such as Xinjiang (LHNM 2010) and in managing foreign aid in Africa (Brautigam, 2009).
[10] “The General Office of State Council’s notice about pairwise aid policy in support of the reconstruction in the disaster areas of Wenchuan earthquake.” (No.31) issued by the state council of China, September 19th, 2008.

At the end of 2011 all pairwise aid projects were completed, and the Chinese media and government announced the reconstruction policy was a success [11](Xinhua News, 2011). During our field interviews with officials, farmers and entrepreneurs, however, a complementary perspective gained shape. It was brought to our attention that prices of non-traded goods—wages, transport, accommodation, food—had risen quickly after domestic aid flowed in, in particular when the deadline of finishing a project approached or when top leaders inspected local progress. Consistent with the prototypical Dutch disease tale we heard stories about workers abandoning the manufacturing sector, opening a snack bar vending local food to construction workers, or engaging in local construction efforts themselves. Various factories closed down as a result, or reduced production levels, because of a perceived shortage of workers. Since product prices did not change much (prices are determined at national or international markets), profits in the manufacturing sector dropped. A few counties set up industrial parks in order to attract manufacturing investment, but these efforts yielded mostly mixed results, partly due to high and unstable wages.

3. Data and Identification Strategy

We use several data sets to test our main hypotheses. We constructed a GDP panel data set covering the period of 2004-2011 based on the *Sichuan Statistical Yearbook* published in 2005 -2012, and take estimates of economic losses due to the earthquake from the 2009 *Sichuan Statistical Yearbook*. We take employment panel data from three waves of the *China Population Census* (1990, 2000, and 2010) and calculate pairwise aid panel data in 2008, 2009 and 2010 from the *China Statistical Yearbooks.*

We group the counties of Sichuan province into four categories: (i) paired disaster counties, (ii) non-paired disaster counties, (iii) non-disaster neighbors of paired disaster

[11] Conference title of "Summary of Supervising and Inspecting Works on the Disaster Relief and Reconstruction of Post- disaster" were held in Chengdu, Sichuan, 4th, May,2011. And People Newspaper reported it on 5th, May, 2011. Available at: http://paper.people.com.cn/rmrb/html/2011-05/05/nw.D110000renmrb_20110505_2-01.htm?div=-1.

counties, and (iv) other non-disaster counties. See the map in the Appendix for the spatial distribution of the first three types of counties in Sichuan province (this spatial pattern is clearly non-random, highlighting the importance of including county fixed effects to control for non-observables that vary across counties). The definition of 18 paired disaster counties (and 18 paired provinces) follows from "*The General Office of State Council's notice about pairwise aid policy in support of the reconstruction in the disaster areas of Wenchuan earthquake*" (2008, No, 53).[12] We define a binary variable 'paired county' that takes a value of "1" if a county received aid from a paired province, and "0" if otherwise. Non-paired disaster counties and non-disaster counties are classified in accordance with "*The State Council issue a notice of overall planning to support Wenchuan's reconstruction policies after earthquake*" (2008, No.31).[13] Hence, we define another binary variable taking the value "1" if a county suffered damages from the earthquake and qualified for support by the central government, but did not receive aid from a paired province. The counties which border any of the 18 paired disaster counties but did not suffer damages by the earthquake are classified as the third group and, as mentioned, there are nine such counties. Finally, the 96 remaining non-disaster counties are listed as the fourth group.

The earthquake happened in 2008, and we commence our analysis by exploiting an annual data set, focusing on the period 2004-2011, provided by the *Sichuan Statistical Yearbook* published in 2005-2012. And four years before earthquake (2004-2007) as our control time, four years after earthquake (2008-2011) as our treatment time. So we define a binary variable "After quake" as 1 if after earthquake, and 0 otherwise. While this yearbook reports annual employment data for three sectors, the *China Population Census* reports employment information at a more disaggregate level and provides us with more information regarding employment in 21 industrial categories. However, these data are only available for

[12] This document was issued by the general office of state council of China, 11th June, 2008.
[13] This document was issued by the state council of China, 19th September, 2008.

1990, 2000 and 2010. We construct an employment panel data set of different industries at the county level in 2000 and 2010 to test our hypothesis, and will also use employment data between 1990 and 2000 as a placebo test.

Key summary statistics of population, economic losses, GDP per capita, and aid flows to the disaster counties are reported in Table 1. Panels A and B list the paired and non-paired disaster counties, respectively. As shown in Panel A, on average, paired counties lost nearly 160,000 *yuan* per capita (or almost USD 23,000), and received 19,981 *yuan* per capita and 4,527 *yuan* per capita in the form of pairwise and civil aid during the period 2008-2010. For some counties, such as Wenchuan, Beichuan and Qingchuan, this inflow of aid greatly exceeded per capita income in 2007. For example, Wenchuan suffered massive damages of 618,269 *yuan* per capita. Pairwise aid was provided by Guangdong province, one of the richest provinces in China, and amounted to 93,711 *yuan* per capita over three years. This transfer is much higher than per capita income in Wenchuan of 26,204 *yuan* in 2007. In comparison, the non-paired disaster counties received much lower civil aid, not mention they were not entitled to any pairwise aid at all. As shown in Panel B in Table 1, total aid per capita in these counties amounts to 1,786 *yuan*, only about 10% of GDP per capita, compared to 182% in the paired counties, although more than half of them (8) suffered more severe damages than the two least damaged paired counties. Table 1 clearly illustrates enormous variation in per capita damages and aid flows between paired and non-paired counties and even within paired counties. For instance, the ratio of pairwise aid to damage ranges from 0.06 in Minzhu County to 0.61 in Songpan County; the ratio of per capita aid to income varies from 0.21 in Chongzhou County to 4.4 in Beichuan County. We will exploit later to probe the impact of aid on manufacturing using the variation.

<< Insert Table 1 about here >>

The earthquake appears to have affected the share of economic sectors in total income as well. Figure 1 summarizes the evolution of the industrial sector (Panel a) and service sector (Panel b) from 2004 until 2011. We distinguish between the four different types of counties introduced above. As shown in Panel A, after the earthquake, the share of industrial GDP in the paired disaster counties dropped significantly in 2008 before it recovered and mirrored the trend of non-paired disaster counties from 2009 to 2011 at a lower trajectory. Note that, in spite of predictions of the Solow model, we do not observe rapid and full recovery in the sense that the local economy bounces back to the pre-shock income path – it appears as if the post-shock income path represents a permanently lower trajectory.

The industrial sector in non-paired disaster and other non-disaster counties (which do not boarder paired disaster counties) grew rather smoothly throughout the period of 2004-2011, without exhibiting a clear structural break. It is apparent that the share of the industrial sector drops in 2008 in the paired disaster counties, but not in the non-paired disaster counties or other non-disaster counties. The non-disaster neighbors of paired disaster counties had a declining trend in the share of industrial GDP from 2006 to 2009 before shifting gear to a growth mode. However, they grew slightly slower than other three types of regions.

An opposite pattern characterizes developments in the service sector. The share of the service industry in paired disaster counties resisted the declining trend and expanded rapidly in 2008, but not in the other three types of counties.[14] After 2009, the service sector deflated smoothly, until all pairwise aid finished in 2011. Interesting, the share of service sector in the non-disaster neighbors of paired disaster counties exhibited a rapid growth from 2008 to 2009 before leveling off, lagging behind the trend of paired disaster counties for one year.

[14] The service sector in the non-disaster counties also experienced a blip in 2009 probably due to the spillover effect of aid to these areas. For example, many supplies were first transported to Chengdu, the capital city, before distributed to the disaster counties. Some non-earthquake counties along the major transport lines might also have benefited from the massive inflow of aid and personnel. These spillover effects will attenuate the economic and statistical significance of our regression below, biasing our findings towards zero.

<< *Insert Figure 1 about here* >>

Table 2 provides the summary statistics of total GDP, GDP per capita, and the share of GDP by sector in 2000 and 2010 for all counties as well as for four subsamples as indicated above. The share of industrial GDP in the paired disaster counties and their non-disaster neighbors have increased by 32.9% and 18.1%, lower than the non-paired disaster counties (40.2%) and other non-disaster counties (51.7%).

<< *Insert Table 2 about here* >>

Table 3 summarizes employment data of different industries in 1990, 2000 and 2010 for Sichuan as a whole and for four subsamples as indicated above.[15] These data are extracted from three population census waves covering all of China, providing detailed information about the population (age, sex, employment, *hukou*, migration, etc.). For our empirical analysis we are interested in four industries: the agricultural sector, manufacturing, the construction sector, and the service sector. Across the board, employment in the agricultural sector has been steadily declining in the counties in our sample. In contrast, the manufacturing, construction and service sectors have experienced rapid growth, especially during the period 2000-2010. Consistent with reports in the (popular) media, the enormous growth in the construction sector in recent years is particularly striking. In comparison, the growth in the industrial employment is lackluster, in particular in the paired disaster counties. In the period of 2000-2010, the share of manufacturing employment in the paired disaster counties grew by 9.3%, much lower than other non-disaster counties (78.8%).

<< *Insert Table 3 about here* >>

[15] Employed persons are adults more than 16 years old. The 1990 census covers the entire population, while only 10% of the population was (randomly) sampled in the 2000 and 2010 census. So we multiply data by 10 to obtain provincial figures. The number of counties in1990 is lower than in 2000 (and 2010) because three new counties were created. Omitting them does not affect the results of our analysis.

Our identification strategy is simple but robust. First, we examine the association between the disaster or aid flow, and (the composition of) GDP at the county level during the period 2004-2011 in a differences-in-difference framework. We estimate a series of models based on the following specification:

$$X_i = \alpha_i + \alpha_1 T_i \times \textit{Post-disaster} + \alpha_2 \textit{Years} + \varepsilon_i \qquad (1)$$

Where X_i measures the logarithm of (per capita) income in county i, α_i captures county fixed effects, T_i is a binary treatment indicator (see below), *Post-disaster* is a binary variable taking the value 1 for post-disaster years (2008-2011), *Years* is a vector of year dummies, and ε is an error term. The indicator variable T_i can capture different "treatments." In all the cases, the control group is other non-disaster counties. In some models T_i=1 indicates that the county is paired. Such a model compares the paired disaster counties to other non-disaster counties. In another model, T_i=1 indicates a non-paired disaster county, so that we examine the effect of centralized aid on (per capita) income for the sub-sample of disaster-struck counties. Since the inflow of state aid is relatively small compared to aid provided by paired provinces, we also expect relatively small effects in the latter analysis. Finally, we consider the spillover effect of the pairwise aid on neighboring counties (T_i=1 indicates a non-disaster county neighboring a paired disaster county).

We also estimate model (1) with a different dependent variable. Rather than explaining variation in income levels, we now seek to explain variation in the sectoral composition of county-level income. That is, the dependent variable X_i captures the share of agriculture income in county-level GDP, the share of industrial (manufacturing) income in GDP, or the share of services in GDP. The Dutch disease hypothesis is consistent with $\alpha_1 < 0$ for models explaining the share of industrial income in county-level GDP, and $\alpha_1 > 0$ for models explaining the share of service income in GDP.

Next, we probe the association between levels of (per capita) aid and various economic variables of interest (or rather, the first difference of these variables over the period 2000-2010—see below). This implies zooming in on the sub-sample of counties that received pairwise aid (N=18), and estimating the following model:

$$X_{it} = \beta_0 + \beta_1 Aid_i + \beta_2 Damages_i + \beta_3 X_{i0} + \varepsilon_i \qquad (2)$$

Where Aid_i measures the inflow of decentralized aid per capita in county *i*, and $Damages_i$ measures the estimated damages per capita due to the earthquake (so as not to confound the effect of aid with the effect of the destruction itself). The specification of the model follows closely the standard growth empirics. As above, dependent variable X_{it} measures the change in (sectoral) income (log) from 2000 to 2010. The initial value of per capita income (log), X_{i0}, is included in equation (2) as a right-hand side variable. However, and closer in spirit to the Dutch disease hypothesis, we also consider the change in sectoral employment (log) as the dependent variable, so that X_{it} measures the growth or decrease of employment in the manufacturing (or service) sector over the period 2000-2010.

We proceed by using data of the *China Population Census* to analyze the impact of various county-level treatments on sectoral employment. These data enables us to increase the sample size, but census data are only available for 2000 and 2010. We estimate the following model:

$$X_i = \alpha_i + \alpha_1 T_i \times Year\_2010 + \alpha_2 Year\_2010 + \varepsilon_i. \qquad (3)$$

Again, X_i measures the share of sectoral employment, and T_i is a binary variable indicating one of a series of possible treatments. As before, we consider whether or not county *i* suffered from the earthquake (either selected for pairwise aid or for state-aid), or whether or not a non-disaster county borders a paired county.

The validity of our identification strategy rests on the following two assumptions: (*i*) households in disaster counties would have experienced similar economic performance in the absence of the disaster and associated inflow of aid as non-disaster counties (the so-called "common trend" assumption of DID models), and (*ii*) the changes we document in the sectoral composition of local economies are due to demand effects, and not by direct damages of the earthquake to local production capacity (e.g., a supply effect caused by destroyed factory buildings). That is, we concede to the possibility that the earthquake locally destroyed physical capital in the same counties that were subsequently targeted for extra help. If so, the correlation between a declining manufacturing sector and aid may be driven by the fact that the manufacturing base was destroyed and needed to be rebuilt. We now discuss these challenges to identification.

First, to probe the common trend assumption we will estimate model (3) using data from the 1990 and 2000 census. This amounts to a placebo test (the coefficient associated with the interaction term should be insignificant), because if the common trend assumption is valid the paired disaster counties, their non-disaster neighbors, or non-paired disaster counties, should not be different than either set of control counties for this period. Second, to distinguish between Dutch disease effects and direct damages, we will divide the non-disaster counties into two groups: 9 non-disaster neighbors of paired disaster counties and 96 other non-disaster counties. The counties bordering the paired disaster counties, though not directly suffering from earthquake damages, were affected by the rising labor and construction material costs in nearby disaster counties (the contagion or spill-over effect). Hence, we use neighboring counties as a treatment group to isolate the channels of "Dutch disease" in a DID analysis, using the other non-disaster counties as a control group. This indirect effect of aid on neighboring counties can be regarded a pure case of "Dutch disease."[16]

Finally, following Rajan and Subramanian (2011) we seek to learn more about the transmission mechanism linking aid to sectoral (under) performance. Our approach is simple, and consists of a comparison of the prices of non-tradables across disaster and non-disaster counties. Prior to the earthquake, we would not expect systematic differences between these two types of areas. However, during the period when aid flowed into the disaster counties, the Dutch disease hypothesis predicts rising (relative) prices of non-tradables. As a proxy for the price of non-tradables we use wages of skilled and unskilled labor, and prices of construction materials. After the cessation of aid, relative prices should adjust again. To probe such dynamics in relative prices, we have collected the price of non-tradables for three years: prior to the earthquake (2007), during the aid period (2009), and after the cessation of aid (2011).

4. Empirical results

After the earthquake struck, the disaster area suffered enormous economic losses, which may result in lower GDP directly (say via destruction of productive capital). Table 4 reports the difference-in-differences estimations of the impact of the earthquake on total and per capita GDP, using data at the county level from 2004 to 2011 and following equation (1). Year and county fixed effects are included in the regressions, but not reported separately. The variable of interest is the interaction term between a dummy variable for treatment (paired, or

[16] Our identification also rests on the assumption that the effect of an inflow of aid decreases with distance from the area receiving aid (i.e., limited mobility of workers across space in response to income differentials). Empirical evidence for other countries suggests this assumption is satisfied—the magnitude of local migration to dissipate income differentials is limited by transaction costs (e.g., Aragon and Rud 2013 for the case of Peru). In China there is considerable rural-urban migration (people moving from the hinterland to coastal metropolitan areas and Beijing) but there is little migration within the hinterland. Another concern is that changes in income reflect compositional changes in the labor force – selective migration into (or out of) disaster areas, inviting changes in average income. Following Aragon and Rud (2013) we probe the issue of selective migration by testing for significant differences in terms of observables between disaster and non-disaster areas. We find no evidence of such differences (details available on request).

non-paired disaster, and non-disaster neighbors of paired disaster counties) and a dummy variable for the period of 2008-2011 (post-earthquake). The control group is other non-disaster counties. In the two samples (paired and non-paired disaster counties), the coefficient for the interaction term is significantly negative. This suggests disaster counties have indeed suffered greater losses in GDP than non-earthquake counties while, as expected, paired disaster counties experienced a much larger decline in income than other counties. The earthquake has reduced total GDP and per capita GDP in paired disaster counties by 3.72% (-0.316/ln(361*13,434/1000)) and 3.18% (-0.302/ln(13,434)), respectively, if using 2007 as a base line. This is equivalent to chopping out more than one percentage points from the normal annual growth rate for three consecutive years after the earthquake. The damages on the non-paired disaster counties are less severe, amounting to about one third of those on the paired disaster counties.

The first three regressions estimate the earthquake impact on GDP impact by comparing paired disaster areas with other non-disaster counties. However, since the paired disaster areas not only suffered physical damages but also received a large amount of aid, it is difficult to distinct the impact of aid on GDP from damages on GDP. To remedy this concern, the two regressions (5 and 6) report the regression results using sample of non-disaster neighbors of paired disaster counties versus other non-disaster counties. Since the treatment in this sample was not subject to direct earthquake damage at all, the observed impact, if any, is not due to the loss in productive capacity during the earthquake. The coefficient on the interaction term is highly significant and negative, indicating that the neighbors of paired disaster counties also suffered losses in GDP, with a magnitude about half of that for paired disaster counties.

<< *Insert Table 4 about here* >>

Since we know that, at the aggregate level, industrial and service GDP evolved differently in paired disaster counties than in other counties (see Figure 1), we next examine the impact of the earthquake on the structure of GDP. For this we make use of variation at the county level, and again control for year and county effects via year and county dummies (not reported). Regression results are reported in Table 5. Once again, we compare the three following counties with control group of other non-disaster counties: (1) paired disaster counties; (2) non-paired disaster counties; (3) non-disaster neighbors of paired disaster counties. For each sample, we run three sets of regressions and try to explain variation in the share of agricultural, industrial, and service GDP, respectively. In Panel A, the coefficient on the interaction term in the regression on the share of industrial GDP(%) is -4.95, significant at the 1% level, suggesting that the earthquake and subsequent aid have caused a drop in the share of industrial GDP in 2010 of paired disaster counties by 10.6% (-4.945/46.61). The coefficient in the regression on service GDP is positive and significant at the 10% level. The earthquake lifts up the share of service GDP in the paired disaster counties by 2.26 percentage points, accounting for 6.9% (2.262/32.79) of the service GDP share in 2010.

In Panel B on the non-paired disaster counties, the interaction term becomes positive yet insignificant. In disaster areas which did not suffer severe damage and were not paired the more lucrative aid package, their share of industrial GDP did not perform much differently from that in other non-disaster counties. It seems when aid flow is modest, the negative impact on industrial production does not materialize.

The results in Panel C are similar to those in Panel A. Even though not directly exposed to earthquake, the neighbors of paired disaster counties suffered even greater loss in the share of industrial GDP than the paired disaster counties (-21.6%=-7.137/33.1). This suggests a quite large negative spillover effect of pairwise aid on neighboring counties. In general, these results in Table 5 are largely consistent with the patterns revealed in Figure 1.

<< *Insert Table 5 about here* >>

These regressions do not control for the intensity of the disaster—the extent of the damages done—which may introduce estimation bias because of omitted variables. To remedy this problem, we run regressions on the change in GDP and employment by sector for a restricted sample of paired disaster counties receiving aid by controlling for losses per capita and aid per capita following the specification of equation (2), and results are reported in Table 6A. In each panel, we consider two specifications, Panel A1 (B1) with separate pairwise aid per capita and civil aid per capita and Panel A2 (or B2) with total aid per capita. In the first set of regressions (Panel A1), the pairwise aid variable enters with a negative yet insignificant sign in the regression on industrial GDP. When total aid is considered in Panel A2, its coefficient turns positive but remains insignificant. Lack of significance may reflect the low power of inference associated with the small sample size and less reliable GDP figures.

<< *Insert Tables 6A and 6B about here* >>

There have been some reports on the inaccuracy of local Chinese GDP figures (e.g., Holz, 2008). For example, the growth in GDP at the provincial level reported by provinces is higher than the national average, suggesting that local governments have manipulated the GDP figures. To check the robustness of the results shown in Table 6A, we further examine the impact of earthquake on the share of sectoral employment in total prime-age population (15-64) using data extracted from the *China Population Census* in 2000 and 2010. The results are presented in Panel B of Table 6A. When both pairwise aid and civil aid are included in Panel B1, the coefficient for aid per capita is -0.407, statistically significant at 1% level, and the one for civil aid is -0.295 significant at 10% level in regressions on manufacturing employment growth. In Panel B2, the two aid variables are replaced by total aid per capita. The coefficient for the variable is -0.552 and highly significant. According to this coefficient, an one-standard deviation increase (1.023) in aid per capita (log) would reduce the share of manufacturing employment by 37.2 percentage points (exp(-0.4552*1.023)-1), accounting for 79.9% of the actual employment share in 2010. In summary, aid greatly hinders employment growth in manufacturing in the paired disaster counties.

Considering that the magnitude of pairwise aid overshadows civil aid, we ask whether the same patterns can be discerned in non-paired disaster counties which received only civil aid. Table 6B repeats the analysis of Table 6A for a restricted sample of non-paired disaster counties. The civil aid variable is insignificant in both the regressions on the share of industrial GDP and manufacturing employment. It appears that the amount of aid in these counties was not big enough to exert a negative impact on industrial development.

One key advantage of samples of paired disaster counties is that we can control for both earthquake damages and aid received. However, the sample has a major limitation — the sample size is very small with only 18 counties. We therefore expand the sample to include non-earthquake counties and non-paired disaster counties from Sichuan Province. Unfortunately, for this sample we cannot include a continuous variable for aid flows, nor can we control for losses. The reason is that the exact aid amount is not available to the public for the non-paired disaster counties. Hence, we adopt a difference-in-differences approach to evaluate the impact of different aid policy on employment growth and follow the specification in equation (3). In Table 7, we compare three types of treatments: (1) paired disaster counties; (2) non-paired versus disaster counties; (3) non-paired neighbors of paired disaster counties.

<< Insert Table 7 about here >>

Table 7 reports the main results on the impact of aid on the sectorial employment share. Again, the interaction term is the main variable of interest. In Panel A we find that paired disaster counties have experienced a significant decline in the share of industrial employment than the control group, the non-disaster counties which do not border any of the paired disaster counties. In specific, a paired disaster county suffered a decline of 1.569 percentage points in the share of manufacturing employment, or 34.9% of the actual manufacturing employment share in 2010 (-1.569/4.49). It appears as if the earthquake and associated pairwise aid inflow have reshaped the trajectory of employment structure. As shown in Panel B, non-paired disaster counties, a subsample of disaster counties, reveal similar patterns as overall paired disaster counties. the coefficient on the interaction term in the subsample of non-disaster neighbors of paired disaster counties as shown in Panel C is greater than that in Panels A and B. The share of manufacturing employment in non-disaster neighbors of paired disaster would have been1.611 percentage points higher, or 70.3% (-1.611/2.29) more than the actual share in 2010, if they luckily happen not to near the paired disaster counties.

Although we have included county and year fixed effects in the above regressions, it is still possible that we failed to capture unobserved factors, influencing disaster counties and non-disaster counties differently. Such omitted variables could result in estimation bias. To mitigate this concern, we run a set of placebo tests using data from *China Population Census* in 1990 and 2000—i.e., prior to the earthquake. If omitted variables are a problem for regressions in the period of 2000-2010, they might equally affect placebo regressions for this early ten-year period, prior to the earthquake. Table 8 presents the results of such placebo regressions for employment by sector in 1990 and 2000. In contrast to the results reported in Table 7 we now find that none of the coefficient for the interaction term in the regressions on manufacturing employment is significant. This suggests that if there are unobserved factors affecting employment in disaster counties, they do not favor or discriminate against the manufacturing sector. Before the earthquake struck, there was no obvious declining trend of manufacturing employment in the disaster counties. We conclude that the decline in manufacturing employment after the earthquake is most likely driven by the quake and associated inflow of aid.

<< *Insert Table 8 about here* >>

So what are the major transmission channels for the declining manufacturing employment in disaster counties? Of course, there are many potential culprits. The simplest explanation would be that the earthquake destroyed part of the industrial base of affected counties—and more so in paired disaster counties than in non-paired ones—casting the manufacturing sector in these counties back to an earlier stage of development. However, we have shown that both the shares of industrial GDP and employment in the neighboring counties of paired disaster counties which did not suffer any damage on their industrial base have also slowed down after the earthquake largely thanks to the spillover effect of massive pairwise aid allocated to the neighboring paired disaster counties. This suggests that pairwise aid makes a contribution to the contraction of industrial sector independent of damages on the productive capacity caused by the earthquake.

Rising cost of living is another one of them. We can probe the nature of the transmission mechanism a little further, using additional data. Anecdotal evidence suggests that, thanks to the massive inflow of aid, there was an acute shortage of skilled workers and construction materials in years after the earthquake. Using data obtained in a recent survey conducted by the Research Center for Rural Economy under Ministry of Agriculture, we tabulate daily wages for unskilled and skilled workers as well as prices for major construction materials (cement, steel, and brick) for three years (2007, 2009, and 2011) in Table 9. Prior to the earthquake, there were no systematic differences in wages and construction material prices as shown in the three columns under year 2007. In 2009, one year after the earthquake and during the period when state and province aid flowed into selected disaster counties, wages for skilled workers and three major construction material prices in disaster counties escalated much faster. They greatly exceeded those in non-disaster counties. It is interesting to note that the price of skilled labor is significantly greater in disaster counties, and that the same is not true for unskilled labor. This reflects the relative scarcity of skilled labor, supporting the market-mediated effect proposed by the Dutch disease hypothesis. In 2011, after the cessation of aid, the wages effect disappears. If anything, it appears as if the prices of these non-tradables now tend to be higher in non-disaster counties than in disaster counties.

To further support our claims with respect to the impact of aid flows on non-tradable prices, we collected hotel price data in Sichuan province from Ctrip, the largest online travel service company. The company did not start online hotel booking service in Sichuan province until October, 2008. The total sample available to us includes 32 hotels in 4 paired disaster counties, 3 hotels in 2 non-paired disaster counties, 3 hotels in 1 non-disaster neighbour of paired disaster, and 55 hotels in 3 other non-disaster counties. We regress the monthly hotel prices on aid flows at the county level in the restricted sample of disaster counties. The results are reported in Table 10. In the first regression, the sample period is from October 2008 to December 2010 and pairwise aid per capita is used. The coefficient for the aid variable is 0.58, significant at 1% level. In the second regression, we include civil aid per capita. Because the civil aid lasted for only two years in 2008 and 2009, the sample period is shortened to October 2008-December 2011. The coefficient for the pairwise aid variable remains positive and highly significant. The coefficient for civil aid is much smaller (0.018), significant at 10% level. In the third regression, we restrict the sample to non-paired disaster counties. Consistent with earlier evidence, civil aid does not affect hotel prices in the non-paired disaster counties, probably because the amounts involved are much smaller.

<< Insert Tables 9 and 10 about here >>

5. Discussion and conclusions

The relation between aid and growth remains contested, and cross-country growth models have been unable to document robust evidence of positive growth effects of aid. One prominent explanation for the absence of such effects is Dutch disease hypothesis, which argues that windfall gains translate into an appreciation of the real exchange rate, which undermines the profitability of the manufacturing sector—arguably the long-term engine of economic growth. However, the link between aid and a shrinking manufacturing sector is under-explored, and in light of considerable heterogeneity in terms of both characteristics of receiving countries and the type of aid that is supplied by donors, the scope for improving our understanding of the nature of transmission mechanisms in a cross-country context may be limited.

In this paper we seek to contribute to the literature on the effectiveness of aid by focusing on a specific form of aid (post-disaster recovery aid) in a specific geographical area (Sichuan province, in China). Indeed, this is one of the first papers to probe the consequences of aid at the meso-level (i.e., the level between "the state" and "individual households"). The nature of the aid we study also implies we cement the tiny and shaky bridge between the two economic literatures on aid and disasters. Until now, the economics of post-disaster recovery is relatively unexplored terrain, largely due to a lack of reliable (historical) data. The recent well-documented process of recovery and reconstruction in China provides us with a good opportunity to gain a better understanding of the economic consequences of relief and rebuilding. Hopefully the research findings will also be relevant for other less fortunate regions. Moreover, this is the first paper to probe Dutch disease type of effects in the context of aid and post-disaster recovery.

Our main question is whether the inflow of aid, and the magnitude of such inflows, is a factor explaining industrial development. To explore this issue, we employ a series of differences-in-difference models, and compare sectoral income and employment in affected and control counties. Our results support the view that the inflow of aid can invite Dutch disease type of processes. Specifically, we find that the inflow of aid causes contraction of the manufacturing sector—both in terms of income and employment—and also document that (temporary) increases in the prices of non-tradables are a potential transmission mechanism linking aid to manufacturing decline. We believe our insights confirm and complement those of Rajan and Subramanian (2011). Of course it is important to realize that aid was delivered on a very large scale—our data demonstrate that per capita inflow of aid for some counties exceeded per capita income levels prior to the disaster. It is no surprise that such massive transfers can invite structural changes in local economies. It remains an urgent priority for future work to verify whether similar effects—albeit possibly at a smaller scale—also materialize in the context of more modest (or typical) aid flows.

The purpose of this paper was not to evaluate the policy impact of pairwise aid policy, or to assess its usefulness as a tool to cope with future disasters. This would require an analysis that considers both the short and long-term effects of the policy, and that would seek to quantify a broad range of costs and benefits associated with the aid flows. Our aim is much more modest, and is restricted to identifying whether aid impacts on industrial growth and the sectoral composition of local economies. Our differences-in-difference analysis enables us to probe this issue when the following two assumptions hold: (i) post-disaster economic growth in paired and non-paired disaster counties would have followed a similar trend in the absence of the disaster and aid provision process, and (ii) aid provision should vary across counties and to some extent be "exogenous" to recipient counties. Our placebo test suggests the former condition is satisfied, and details of the pairwise aid policy imply that the latter assumption is also likely to be true. Hence, we find evidence of a case of "doing bad by doing good" associated with humanitarian aid.

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Table 1. Pairwise and civil aid

Paired county	Pairwise province	Population in 2008 (Thousand person)	Losses per capita (*yuan*)	GDP per capita in 2007(*yuan*)	Pairwise aid per capita (*yuan*)	Civil aid per capita(*yuan*)
Panel A: Paired disaster counties						
Wenchuan Xian	Guangdong	104	618,269	26,204	93,711	8,679
Mianzhu Shi	Jiangsu	514	276,848	28,863	15,949	5,968
Dujiangyan Shi	Shanghai	612	81,699	18,568	11,395	3,302
Beichuan Xian	Shandong	154	383,766	8,598	37,864	5,955
Qingchuan Xian	Zhejiang	246	203,577	6,107	23,274	6,399
Shifang Shi	Beijing	433	205,312	29,703	12,371	4,935
An Xian	Liaoning	515	83,573	10,434	7,825	6,054
Jiangyou Shi	Henan	883	9,060	16,438	3,394	3,725
Pingwu Xian	Hebei	186	92,366	9,366	15,074	4,406
Pengzhou Shi	Fujian	800	34,125	14,028	3,082	2,435
Mao Xian	Shanxi	109	200,000	9,512	19,741	5,075
Songpan Xian	Anhui	73	47,671	11,596	29,209	2,231
Hanyuan Xian	Hubei	321	16,760	6,972	6,592	2,273
Li Xian	Hunan	46	309,750	13,245	36,492	9,662
Chongzhou Shi	Chongqing	670	15,642	12,280	2,501	679
Jiange Xian	Heilongjiang	684	29,678	5,762	2,427	1,951
Xiaojin Xian	Jiangxi	80	172,500	5,770	18,247	3,211
Heishui Xian	Jilin	60	78,758	8,367	20,510	4,543
Average		361	158,853	13,434	19,981	4,527
Panel B: Non-paired disaster counties						
Zitong Xian		382	28,123	8,287		3,123
Wangcang Xian		460	26,935	7,306		2,361
Luojiang Xian		246	47,154	12,839		3,482
Santai Xian		1474	20,037	7,402		1,593
Langzhong Shi		877	1,311	8,570		1,170
Yanting Xian		609	15,076	7,138		2,222
Cangxi Xian		788	6,044	5,884		1,262
Lushan Xian		119	9,748	10,541		377
Zhongjiang Xian		1427	9,239	8,959		1,096
Dayi Xian		517	13,540	12,726		189
Baoxing Xian		58	34,586	15,911		1,097
Nanjiang Xian		671	2,216	5,699		735
Guanghan Shi		597	19,095	18,571		825
Shimian Xian		121	13,967	19,483		1,380
Jiuzhaigou Xian		65	123,077	17,807		1,786

Note:
1. Pairwise aid in 2008, 2009 and 2010 in each county amounts to 1% of the paired province's general budget revenue in 2007, 2008, and 2009, separately. Aid per capita=total aid/total population in 2008. The revenue data are from *China Statistical Yearbook* (2008, 2009, and 2010).
2. Population and income data come from *Sichuan Statistical Yearbook* (2008, 2009, 2010, and 2011).
3. Total losses are from *Sichuan Yearbook* (2009); losses per capita=total losses/total population in 2008.
4. Total civil aid comes from *Sichuan Civil Affairs Statistical Yearbook* (2009 and 2010).

Table 2. Summary statistics of GDP by sector, county level

Industry	2000		2010		Growth
	Mean	Std. Dev.	Mean	Std. Dev.	2000-2010 (%)
Panel A: All counties					
GDP, million yuan	1,846	2,342	6,738	6,898	265.06
GDP per Capita, yuan	3,832	2,421	15,733	7,846	310.54
Share of agriculture GDP (%)	37.58	13.64	25.10	10.04	-33.21
Share of industrial GDP (%)	30.40	13.70	44.23	15.35	45.49
Share of Service GDP (%)	31.37	9.15	30.67	9.28	-2.22
Counties	138		138		
Panel B: Paired disaster counties					
GDP, million yuan	2,379	2,526	6,188	5,944	160.06
GDP per Capita, yuan	5,500	3,301	16,654	7,507	202.77
Share of agriculture GDP (%)	31.28	13.47	20.60	8.20	-34.13
Share of industrial GDP (%)	35.08	16.00	46.61	13.63	32.86
Share of Service GDP (%)	33.64	7.65	32.79	9.34	-2.54
Counties	18		18		
Panel C: Non-paired disaster counties					
GDP, million yuan	2,141	1,668	7,093	5,180	231.30
GDP per Capita, yuan	4,930	2,567	17,137	7,193	247.57
Share of agriculture GDP (%)	35.80	14.63	24.81	9.54	-30.70
Share of industrial GDP (%)	33.09	15.16	46.37	13.31	40.15
Share of Service GDP (%)	31.12	11.45	28.82	9.81	-7.38
Counties	15		15		
Panel D: Non-disaster neighbours of paired disaster counties					
GDP, million yuan	942	1,799	2,367	3,211	151.30
GDP per Capita, yuan	4,692	2,515	15,269	6,104	225.41
Share of agriculture GDP (%)	32.19	20.48	25.67	14.16	-20.27
Share of industrial GDP (%)	28.03	17.55	33.10	16.37	18.06
Share of Service GDP (%)	39.78	18.86	41.24	13.92	3.67
Counties	9		9		
Panel E: Other non-disaster counties					
GDP, million yuan	1,784	2,436	7,195	7,442	303.28
GDP per Capita, yuan	3,267	1,972	15,385	8,204	370.87
Share of agriculture GDP (%)	39.54	12.42	25.93	9.93	-34.41
Share of industrial GDP (%)	29.32	12.57	44.49	15.63	51.72
Share of Service GDP (%)	30.20	7.21	29.58	8.06	-2.06
Counties	96		96		

Note:
GDP in 2000 and 2010 is obtained from *Sichuan Statistical Yearbooks* published in 2001 and 2011. “Paired disaster” is defined as 1 if a county received pairwise aid funds according the policy issued by the general office of state council of China (11th June, 2008), 0 otherwise; “Non-paired disaster” is defined as 1 if a disaster county did not receive pairwise aid funds according the policy issued by the state council of China (19th September, 2008), 0 otherwise. “Non-disaster neighbors of paired disaster” are defined as 1, if they border at least one of the paired disaster counties but did not suffer the earthquake, 0 otherwise. “Other non-disaster” is defined as 1, if a county did not suffer the earthquake and far away from the paired disaster counties, 0 otherwise.

Table 3. Summary statistics of employment by sector, averaged at the county level

Industry	1990 Mean	1990 Std. Dev.	2000 Mean	2000 Std. Dev.	2010 Mean	2010 Std. Dev.	Growth 1990-2000 (%)	Growth 2000-2010 (%)
Panel A All counties								
Prime-age working population (15-64)	305,249	272,754	295,761	252,218	283,808	232,479	-3.11	-4.04
Employment rate (%)	90.57	3.04	85.28	7.85	85.14	9.52	-5.85	-0.16
Share of agriculture, forestry, animal husbandry and fishery (%)	77.19	8.14	70.94	10.75	62.08	14.90	-8.10	-12.49
Share of manufacturing (%)	2.93	2.50	2.78	2.61	4.29	3.98	-4.94	54.18
Share of construction (%)	0.52	0.51	0.84	0.77	3.83	2.94	61.86	355.98
Share of service (%)	8.12	3.89	9.71	3.86	13.68	4.50	19.61	40.89
Counties	135		138		138			
Panel B Paired disaster counties								
Prime-age working population (15-64)	240,945	192,988	255,308	200,808	248,751	193,000	5.96	-2.57
Employment rate (%)	90.42	2.65	88.04	5.95	80.90	9.75	-2.63	-8.11
Share of agriculture, forestry, animal husbandry and fishery (%)	74.18	7.35	70.57	10.42	55.01	16.24	-4.88	-22.04
Share of manufacturing (%)	4.36	3.83	4.11	3.36	4.49	4.10	-5.80	9.26
Share of construction (%)	0.76	0.72	1.08	0.65	4.36	2.17	42.05	304.74
Share of service (%)	8.60	2.16	11.02	2.58	16.15	4.87	28.13	46.57
Counties	18		18		18			
Panel C Non-paired disaster counties								
Prime-age working population (15-64)	417,294	290,416	379,031	296,948	331,855	242,640	-9.17	-12.45
Employment rate (%)	89.58	3.67	83.20	5.95	81.36	10.62	-7.12	-2.22
Share of agriculture, forestry, animal husbandry and fishery (%)	76.47	9.15	66.73	7.10	56.40	14.33	-12.74	-15.48
Share of manufacturing (%)	3.71	2.49	3.67	2.68	4.42	2.69	-0.99	20.25
Share of construction (%)	0.53	0.48	1.23	0.86	4.94	2.59	130.15	302.80
Share of service (%)	6.80	2.14	10.24	3.72	14.30	3.74	50.57	39.66
Counties	13		15		15			
Panel D Non-disaster neighbours of paired disaster counties								
Prime-age working population (15-64)	93,553	138,108	97,302	137,095	103,817	137,204	4.01	6.70
Employment rate (%)	86.89	3.01	85.91	5.45	79.39	5.55	-1.12	-7.59
Share of agriculture, forestry, animal husbandry and fishery (%)	65.32	10.38	66.69	10.02	56.28	9.32	2.09	-15.61
Share of manufacturing (%)	2.85	1.25	1.95	1.42	2.29	1.99	-31.61	17.31
Share of construction (%)	0.84	0.49	0.90	0.65	2.76	1.70	6.45	208.01
Share of service (%)	13.86	6.02	15.26	5.37	17.04	5.72	10.07	11.67
Counties	9		9		9			
Panel E Other non-disaster counties								
Prime-age working population (15-64)	322,155	282,522	308,940	254,230	299,747	238,936	-4.10	-2.98
Employment rate (%)	91.09	2.77	85.02	8.52	87.07	9.06	-6.66	2.40
Share of agriculture, forestry, animal husbandry and fishery (%)	78.99	6.80	72.07	11.20	64.84	14.50	-8.76	-10.03
Share of manufacturing (%)	2.56	2.18	2.48	2.44	4.42	4.24	-3.22	78.75
Share of construction (%)	0.44	0.44	0.73	0.77	3.66	3.16	65.48	401.18
Share of service (%)	7.66	3.66	8.86	3.44	12.80	4.14	15.65	44.51
Counties	95		96		96			

Note:
The employment data are from *China Population Census* in 1990, 2000, and 2010. The employment information in the 1990 census covers the entire population, while only 10% of populations were sampled to answer the question in the 2000 and 2010 census. So we times 10 for the numbers in 2000 and 2010 to obtain the provincial aggregate figures. The number of counties in1990 are 3 fewer than that in 2000 and 2010 because of the creation of new counties in later year. “Paired disaster” is defined as 1 if a county received pairwise aid funds according the policy issued by the general office of state council of China (11th June, 2008), 0 otherwise; “Non-paired disaster” is defined as 1 if a disaster county did not receive pairwise aid funds according the policy issued by the state council of China (19th September, 2008), 0 otherwise. “Non-disaster neighbors of paired” are defined as 1, if they border at least one of the paired disaster counties but did not suffer the earthquake, 0 otherwise. “Other non-disaster” is defined as 1, if a county did not suffer the earthquake and far away from the paired disaster counties, 0 otherwise.

Table 4. Impact of the earthquake on GDP

	Paired versus Other non-disaster		Non-paired disaster versus Other non-disaster		Non-disaster neighbors of paired versus Other non-disaster	
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(GDP)	Log(GDP per capita)	Log(GDP)	Log(GDP per capita)	Log(GDP)	Log(GDP per capita)
Treatment*After quake	-0.316***	-0.302***	-0.128***	-0.095*	-0.109***	-0.150***
	(0.048)	(0.047)	(0.045)	(0.049)	(0.041)	(0.041)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
County dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	912	912	888	888	840	840
Adj. R^2	0.935	0.929	0.948	0.940	0.950	0.941

Note:
GDP from 2004 to 2011 is obtained from *Sichuan Statistical Yearbooks* published from 2005 to 2012. The county and year fixed effects are included in regressions but not reported here. "Paired disaster" is defined as 1 if a county received pairwise aid funds according the policy issued by the general office of state council of China (11th June, 2008), 0 otherwise; "Non-paired disaster" is defined as 1 if a disaster county did not receive pairwise aid funds according the policy issued by the state council of China (19th September, 2008), 0 otherwise. "Non-disaster neighbors of paired disaster" are defined as 1, if they border at least one of the paired disaster counties but did not suffer the earthquake, 0 otherwise. "Other non-disaster" is defined as 1, if a county did not suffer the earthquake and far away from the paired disaster counties, 0 otherwise. "After quake" is a dummy variable defined as 1 if the time is after earthquake (2008, 2009, 2010, and 2011), and 0 otherwise. County cluster standard errors are reported; * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level.

Table 5. Impact of the earthquake on the share of GDP by sector

	(1)	(2)	(3)
	Share of agriculture GDP	Share of industrial GDP	Share of service GDP
Panel A: Paired versus Other non-disaster counties			
Paired * After quake	2.684**	-4.945***	2.262*
	(1.212)	(1.691)	(1.220)
N	912	912	912
Adj. R^2	0.514	0.521	0.270
Panel B: Non-paired disaster versus Other non-disaster counties			
Non-paired disaster * After quake	-0.165	1.058	-0.893
	(1.116)	(1.078)	(0.833)
N	888	888	888
Adj. R^2	0.546	0.585	0.341
Panel C: Non-disaster neighbors of paired versus Other non-disaster counties			
Non-disaster neighbors of paired * After quake	5.153***	-7.137***	1.984
	(1.215)	(1.452)	(1.325)
N	840	840	840
Adj. R^2	0.524	0.545	0.319

Note:
GDP from 2004 to 2011 is obtained from *Sichuan Statistical Yearbooks* published from 2005 to 2012. “Paired disaster” is defined as 1 if a county received pairwise aid funds according the policy issued by the general office of state council of China (11th June, 2008), 0 otherwise; “Non-paired disaster” is defined as 1 if a disaster county did not receive pairwise aid funds according the policy issued by the state council of China (19th September, 2008), 0 otherwise. “Non-disaster neighbors of paired” are defined as 1, if they border at least one of the paired disaster counties but did not suffer the earthquake, 0 otherwise. “Other non-disaster” is defined as 1, if a county did not suffer the earthquake and far away from the paired disaster counties, 0 otherwise. “After quake” is a dummy variable defined as 1 if the time is after earthquake (2008, 2009, 2010, and 2011), and 0 otherwise. The county and year fixed effects are included in regressions but not reported here. County cluster standard errors are reported. * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level.

Table 6a. Effects of earthquake losses and aid on GDP and employment growth from 2000 to 2010 in disaster counties receiving pairwise aid

	Panel A: Impact on the Share of GDP			
	(1)	(2)		(3)
	Δ Log(% of agriculture GDP)	Δ Log(% of industrial GDP)		Δ Log(% of service GDP)
	Panel A1: The effects of pairwise and civil aid			
Log (pairwise aid per capita)	-0.269**	-0.013		0.107
	(0.107)	(0.110)		(0.082)
Log(civil aid per capita)	-0.195**	0.233*		-0.182
	(0.074)	(0.129)		(0.111)
Log (loss per capita)	0.124	-0.021		-0.009
	(0.079)	(0.079)		(0.080)
N	18	18		18
R^2	0.705	0.679		0.275
	Panel A2: Total aid effects			
Log (total aid per capita)	-0.371**	0.050		0.079
	(0.125)	(0.148)		(0.120)
Log (loss per capita)	0.085	0.032		-0.042
	(0.083)	(0.097)		(0.073)
N	18	18		18
R^2	0.686	0.624		0.165
	Panel B: Impact on the Share of Employment			
	(1)	(2)	(3)	(4)
	Δ Log(% of agri. employment)	Δ Log(% of manu. employment)	Δ Log(% of constr. employment)	Δ Log(% of service employment)
	Panel B1: The effects of pairwise and civil aid			
Log (pairwise aid per capita)	0.002	-0.406***		-0.234
	(0.056)	(0.117)		(0.186)
Log(civil aid per capita)	0.266**	-0.295*		-0.020
	(0.095)	(0.139)		(0.204)
Log (loss per capita)	-0.120**	0.249*		0.197
	(0.055)	(0.117)		(0.195)
N	18	18		18
R^2	0.602	0.601		0.271
	Panel B2: Total aid effects			
Log (total aid per capita)	0.102	-0.552***	-0.238	-0.111
	(0.106)	(0.135)	(0.167)	(0.154)
Log (loss per capita)	-0.074	0.185	0.172	0.012
	(0.060)	(0.127)	(0.175)	(0.109)
N	18	18	18	18
R^2	0.411	0.562	0.250	0.111

Note:
The GDP in year 2000 and 2010 of Panel A is obtained from *Sichuan Statistical Yearbooks* published in 2001 and 2011. The sectoral share of employment in total prime-age population (15-64) in Panel B is calculated by authors using *China Population Census* in 2000 and 2010. Pairwise aid is computed from *China Statistical Yearbooks* (2008, 2009 and 2010). Civil aid is obtained from *Sichuan Civil Affairs Statistical Yearbook*s (2009 and 2010). Total aid includes pairwise aid and civil aid. Total earthquake losses are extracted from *Sichuan Yearbook* in 2009. The initial values of dependent variables are included in the regressions, but not reported here. Robust standard errors are reported. * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level.

Table 6b. Effects of earthquake losses and aid on GDP and employment growth from 2000 to 2010 in non-paired disaster counties

	Panel A: Impact on the Share of GDP			
	(1)	(2)		(3)
	Δ Log(% of agriculture GDP)	Δ Log(% of industrial GDP)		Δ Log(% of service GDP)
Log (civil aid per capita)	-0.107	0.054		0.035
	(0.154)	(0.077)		(0.044)
Log (loss per capita)	0.034	-0.053		-0.013
	(0.069)	(0.035)		(0.030)
N	15	15		15
R^2	0.208	0.708		0.162
	Panel B: Impact on Share of Employment			
	(1)	(2)	(3)	(4)
	Δ Log(% of agri. employment)	Δ Log(% of manu. employment)	Δ Log(% of constr. employment)	Δ Log(% of service employment)
Log (civil aid per capita)	0.217***	-0.108	-0.533*	-0.051
	(0.028)	(0.119)	(0.293)	(0.073)
Log (loss per capita)	-0.138**	-0.174	-0.016	0.030
	(0.060)	(0.124)	(0.112)	(0.075)
N	15	15	15	15
R^2	0.598	0.422	0.732	0.587

Note:
The GDP in year 2000 and 2010 of Panel A is obtained from *Sichuan Statistical Yearbooks* published in 2001 and 2011. The sectoral share of employment in total prime-age population (15-64) in Panel B is calculated by authors using *China Population Census* in 2000 and 2010. Pairwise aid is calculated from *China Statistical Yearbooks* (2008, 2009 and 2010). Civil aid is obtained from *Sichuan Civil Affairs Statistical Yearbook* (2009 and 2010). Total aid includes pairwise aid and civil aid. Total earthquake losses are extracted from *Sichuan Yearbook* in 2009. The initial values of dependent variables are included in the regressions, but not reported here. Robust standard errors are reported. * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level.

Table 7. Impact of the earthquake on the share of employment by sector based on China Population Census in 2000 and 2010

	(1)	(2)	(3)	(4)
	% of Agri. employment	% of Manu. employment	% of Constr. employment	% of Service employment
Panel A: Paired versus Other non-disaster counties				
Paired * Year_2010	-8.326**	-1.569*	0.355	1.190
	(3.312)	(0.935)	(0.715)	(1.341)
N	228	228	228	228
Adj. R^2	0.776	0.621	0.428	0.676
Panel B: Non-paired disaster versus Other non-disaster counties				
Non-paired disaster * Year_2010	-3.099	-1.205*	0.784	0.117
	(4.213)	(0.721)	(1.045)	(1.014)
N	222	222	222	222
Adj. R^2	0.747	0.608	0.411	0.683
Panel C: Non-disaster neighbors of paired disaster versus Other non-disaster counties				
Non-disaster neighbors of paired disaster *	-3.180	-1.611**	-1.061	-2.161
Year_2010	(2.837)	(0.665)	(0.676)	(1.909)
N	210	210	210	210
Adj. R^2	0.769	0.596	0.397	0.700

Note:
The employment data come from *China Population Census* in 2000 and 2010. The employment variable is the share of sectoral employment in total prime-age working population (15-64). "Paired disaster" is defined as 1 if a county received pairwise aid funds according the policy issued by the general office of state council of China (11th June, 2008), 0 otherwise; "Non-paired disaster" is defined as 1 if a disaster county did not receive pairwise aid funds according the policy issued by the state council of China (19th September, 2008), 0 otherwise. "Non-disaster neighbors of paired disaster" are defined as 1, if they border at least one of the paired disaster counties but did not suffer the earthquake, 0 otherwise. "Other non-disaster" is defined as 1, if a county did not suffer the earthquake and far away from the paired disaster counties, 0 otherwise. "Year_2010" is defined as 1, if year is in 2010, 0 otherwise. The county and year fixed effects are included in regressions but not reported here. County cluster standard errors are reported; * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level.

Table 8. Placebo test: The impact of the earthquake on the share of employment by sector based on China Population Census in 1990 and 2000 (prior to earthquake)

	(1)	(2)	(3)	(4)
	% of Agri. employment	% of Manu. employment	% of Constr. employment	% of Service employment
Panel A: Paired versus Other non-disaster counties				
Paired *Year_2000	3.293	-0.178	0.034	1.209**
	(2.721)	(0.548)	(0.236)	(0.584)
N	226	226	226	226
Adj. R^2	0.446	0.847	0.370	0.755
Panel B: Non-paired disaster versus Other non-disaster				
Non-paired disaster * Year_2000	-2.648	-0.083	0.442	1.210*
	(3.153)	(0.579)	(0.281)	(0.630)
N	216	216	216	216
Adj. R^2	0.439	0.816	0.369	0.745
Panel C: Non-disaster neighbors of paired disaster versus Other non-disaster counties				
Non-disaster neighbors of paired disaster * Year_2000	8.273**	-0.827	-0.231	0.185
	(3.178)	(0.759)	(0.281)	(0.893)
N	208	208	208	208
Adj. R^2	0.468	0.793	0.319	0.814

Note:
The employment data come from *China Population Census* in 1990 and 2000. The employment variable is the share of sectoral employment in total prime-age working population (15-64). The sample size is less than Table7 caused by 3 counties in year 1990 fewer than that in 2000 and 2010, 2 counties are non-paired disasters, 1 county is other non-disaster, because of the creation of new counties in later years. “Paired disaster” is defined as 1 if a county received pairwise aid funds according the policy issued by the general office of state council of China (11th June, 2008), 0 otherwise; “Non-paired disaster” is defined as 1 if a disaster county did not receive pairwise aid funds according the policy issued by the state council of China (19th September, 2008), 0 otherwise. “Non-disaster neighbors of paired disaster” are defined as 1, if they border at least one of the paired disaster counties but did not suffer the earthquake, 0 otherwise. “Other non-disaster” is defined as 1, if a county did not suffer the earthquake and far away from the paired disaster counties, 0 otherwise. “Year_2000” is defined as 1, if year is in 2000, 0 otherwise. The county and year fixed effects are included in regressions but not reported here. County cluster standard errors are reported; * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level.

Table 9. Summary statistics of wages and construction material prices in Sichuan Province

	2007			2009			2011		
	Disaster	Non-disaster	p-value	Disaster	Non-disaster	p-value	Disaster	Non-disaster	p-value
Daily wage for unskilled workers (*yuan*)	32.3	34.0	0.703	61.9	57.0	0.471	68.1	80.5	0.044**
Daily wage for skilled workers (*yuan*)	55.0	56.5	0.823	105	85.0	0.027**	111.2	126.5	0.076*
Cement price (*yuan per 1,000kg*)	305.0	298.0	0.801	475	365.5	0.001***	357.7	367.0	0.701
Steel price (*yuan per 1,000kg*)	3,571	3,539	0.933	4,800	3,983.3	0.023**	4,038	4,267	0.514
Brick price (*yuan per piece*)	0.22	0.26	0.149	0.5	0.37	0.017**	0.32	0.41	0.015***

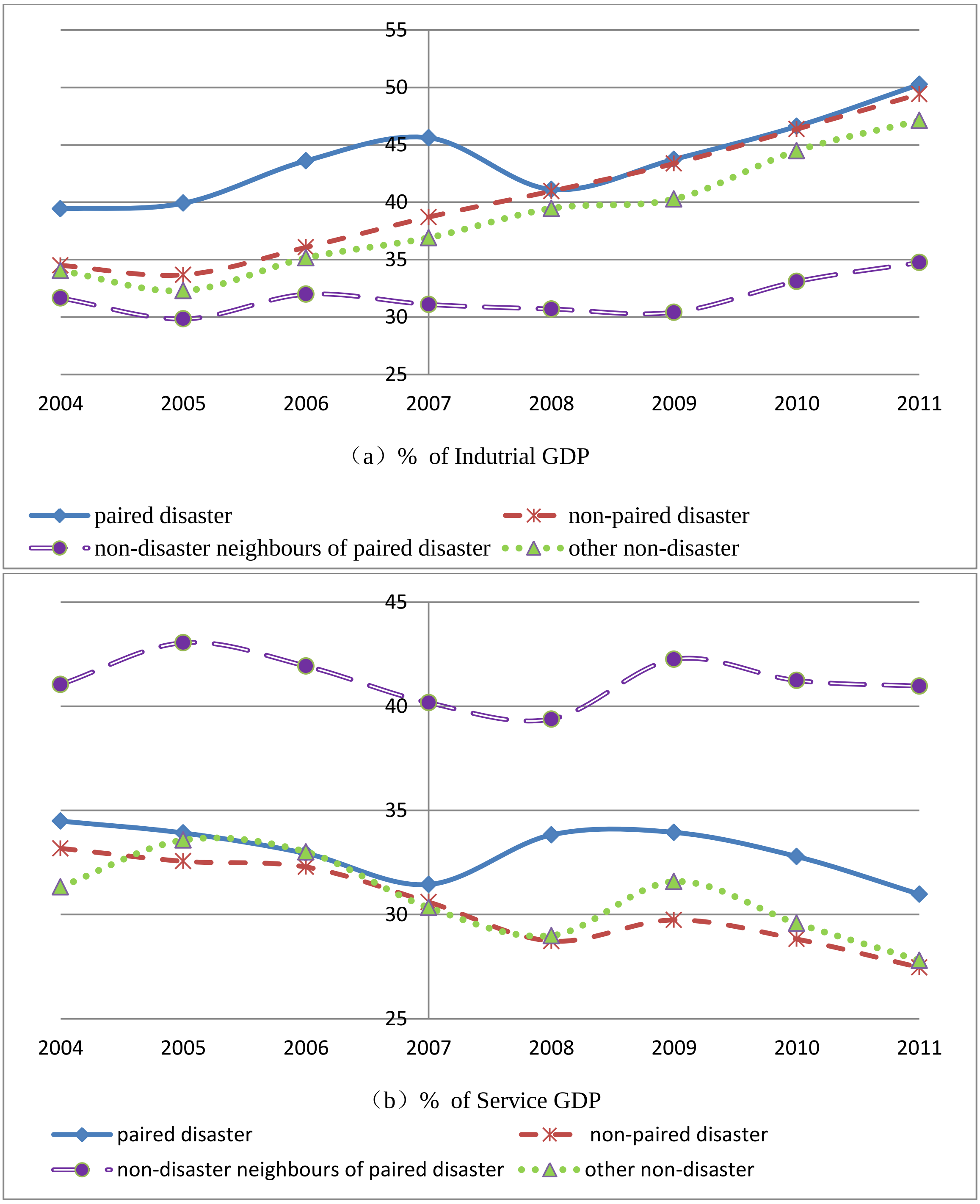
Note:
Computed by authors based on Research Center of Rural Economy (RCRE) survey data in 2011.

Table 10. Effects of aid on monthly hotel price in disaster counties

	Paired disaster 2008-2010	Paired disaster 2008-2009	Non-paired disaster 2008-2009
	(1)	(2)	(3)
	Log(hotel price)	Log (hotel price)	Log (hotel price)
Log (pairwise aid per capita)	0.580***	0.569***	
	(0.016)	(0.006)	
Log (civil aid per capita)		0.018*	-0.085
		(0.005)	(0.105)
Log (neighbors' pairwise aid per capita)			
Log (GDP per capita)	-0.442***	-0.280***	0.308
	(0.065)	(0.006)	(0.520)
Monthly fixed effect	Yes	Yes	Yes
N	73	35	27
R^2	0.960	0.985	0.559

Note:
Pairwise aid is calculated from *China Statistical Yearbooks* (2008, 2009 and 2010). Civil aid is obtained from *Sichuan Civil Affairs Statistical Yearbook* (2009 and 2010). Total aid includes pairwise aid and civil aid. Hotel price comes from the Ctrip, the largest online travel service company in China. The company did not start online hotel booking service in Sichuan province until October, 2008. The total sample available to us includes 32 hotels in 4 paired disaster counties, and 3 hotels in 2 non-paired disaster counties. The hotel price data set is unbalanced panel. We use the monthly average prices for standard rooms at the county level (yuan per day per room). Month dummies are included in the model, but not reported here. County cluster standard errors are reported in column (1), (2) and (3). * denotes significance at 10% level, ** significance at 5% level, *** significance at 1% level.

Figure 1. Share of GDP by sector in different types of counties

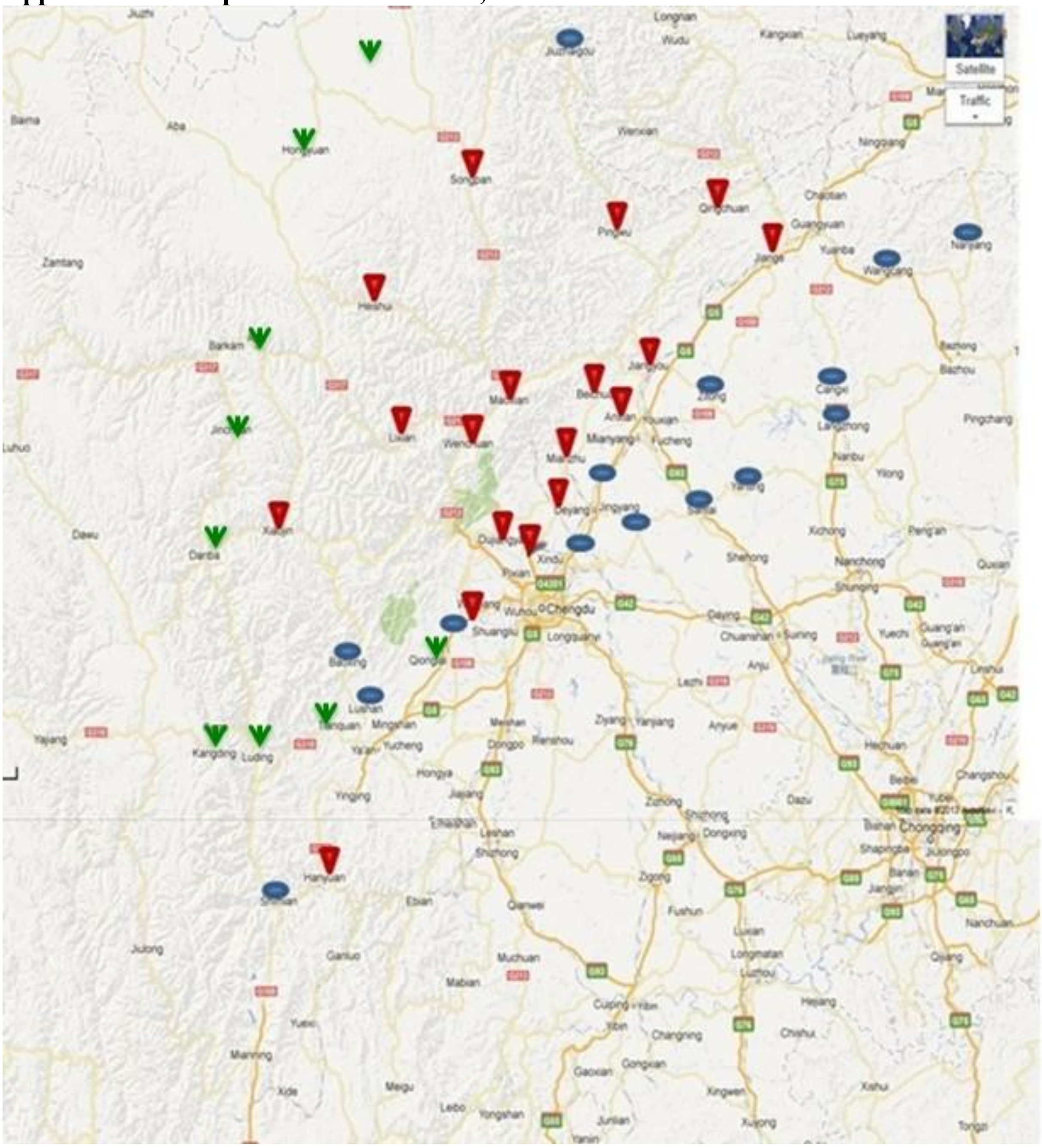


（a） % of Indutrial GDP

（b） % of Service GDP

Note:
Data from 2004 to 2011 comes from *Sichuan Statistical Yearbook* published from 2005 to 2012; "Paired disaster" is defined as 1 if a county received pairwise aid funds according the policy issued by the general office of state council of China (11th June, 2008), 0 otherwise; "Non-paired disaster" is defined as 1 if a disaster county did not receive pairwise aid funds according the policy issued by the state council of China (19th September, 2008), 0 otherwise. "Non-disaster neighbors of paired disaster" are defined as 1, if they border at least one of the paired disaster counties but did not suffer the earthquake, 0 otherwise. "Other non-disaster" is defined as 1, if a county did not suffer the earthquake and far away from the paired disaster counties, 0 otherwise.

Appendix: The map of Sichuan Province, China.



Paired disaster (18) ; Non-paired disaster (15); Non-disaster neighbours of paired disaster (9)