European Journal of Political Economy 45 (2016) 1–17

Contents lists available at ScienceDirect

European Journal of Political Economy

journal homepage: www.elsevier.com/locate/ejpe

The economic effects of a counterinsurgency policy in India: A synthetic control analysis

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ARTICLE INFO

Article history:
Received 12 January 2016
Received in revised form 31 August 2016
Accepted 31 August 2016
Available online 3 September 2016

JEL classification:
H56
F52
D74
O11

Keywords:
Synthetic control method
Counterinsurgency
Conflict
Naxalite insurgency
India

ABSTRACT

Using the synthetic control method, we analyze the economic effects of a unique counterinsurgency response to the Naxalite insurgency in India. Of all the states affected by Naxalite violence, only one state, Andhra Pradesh, raised a specially trained and equipped police force in 1989 known as the Greyhounds, dedicated to combating the Naxalite insurgency. Compared to a synthetic control region constructed from states affected by Naxalite violence that did not raise a similar police force, we find that the per capita NSDP of Andhra Pradesh increased significantly over the period 1989–2000. Further, we find that the effects on the manufacturing sector are particularly strong. Placebo tests indicate that these results are credible and various difference-in-difference specifications using state and industry level panel data further corroborate these findings.

1. Introduction

Since its independence in 1947, India has faced numerous insurgencies within its borders at various points in time. One of the longest running insurgencies in India is the Naxalite – also known as the Maoist – movement. With the ultimate objective of overthrowing the state by force and establishing a communist regime (Ramana, 2009; Gupta, 2007), the Naxalite movement started in a small village in West Bengal in 1967, and then spread steadily across the country. The insurgency was estimated to be spread over 182 districts in 16 states in 2007 (Ramana, 2009) and account for about 91% of the total violence in India and 89% of the resulting deaths (Government of India, 2005) prompting the former Prime Minister Dr. Manmohan Singh to observe that the Naxalite insurgency is the single biggest internal security threat facing the country.

Of the several states in India that are affected by Naxalite violence, only one state, Andhra Pradesh, raised a specially trained police force dedicated to combating the Naxalite insurgency in 1989. This explicit change in the government's counterinsurgency policy gives us a unique opportunity to analyze the effects of this robust localized security response to the Naxalite insurgency, which has not been previously analyzed. In order to do so we apply the synthetic control methodology (Abadie and Gardeazabal, 2003; Abadie et al., 2010), a recently developed generalization of the difference-in-difference methodology, to get

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http://dx.doi.org/10.1016/j.ejpoleco.2016.08.012
0176-2680/

around the standard problems of data and sample size limitations faced by empirical studies of interventions such as this that typically occur at the aggregate level.

We find that the introduction of a specialized police force called "Greyhounds" in Andhra Pradesh (AP) in 1989 is associated with an increase in its per capita net state domestic product (pcNSDP) over the period 1989–2000. Further, we find that this is driven by the various subsectors of the non-agricultural sector and that the effects on the manufacturing sector (both registered and unregistered) are particularly strong. Placebo tests indicate that our results are credible. Additionally, these results are robust to various difference-in-difference regression specifications using state and industry level panel data.

While the relationship between insurgency and economic growth is well established in the security economics literature, the economic effects of counterinsurgency policies remain underexplored (Brück and Schneider, 2011). This paper makes two important contributions. First, by analyzing a counterinsurgency policy in India, it builds on the line of work that uses economic indicators to evaluate the effectiveness of security policies in other parts of the world. While state response to insurgencies has been largely examined in terms of effects on the levels of violence, researchers and practitioners have argued that progress of counterinsurgency methods is better assessed via their effect on economic outcomes (Kapstein, 2012). Conflicts cause political instability which negatively affects savings and investment in the economy. Counterinsurgency polices, by reducing uncertainties and boosting confidence of civilians may enhance investment and economic activity (Naor, 2015). If markets efficiently aggregate information, they can be a good indicator of civilians' security outlook and provide an unbiased evaluation of the state's security policy. Further, we also make a methodological contribution by showing how the synthetic control methodology can be applied to study such policies.

Secondly, we also contribute to the study of conflicts in India. Despite now running in its fifth decade, there exist few systematic quantitative studies on the Naxalite insurgency. Cross-sectional studies find poverty, illiteracy, land inequality, forest cover and population share of marginalized castes and tribes to be the main correlates of Naxalite activity at the district level (Borooah, 2008; Iyer, 2009; Gomes, 2015; Hoelscher et al., 2012). Gawande et al. (2015) in a panel data study find that a one standard deviation decrease in renewable resources increased deaths related to the insurgency by nearly 60 percent over the period 2001–2008. Vanden Eynde (2016) finds negative rainfall shocks to increase Naxalite violence against civilians in order to deter them from becoming police informers. The effects of the recent introduction of a large public-works program (the National Rural Employment Guarantee Scheme) on Naxalite violence are mixed: while Dasgupta et al. (2016) find that it decreased conflict, Khanna and Zimmermann (2015) find that it induced an increase in violence in the short-run (possibly due to civilians providing greater information to the police). In the context of the Punjab insurgency during 1980–1993, Singh (2013) finds conflict to reduce long-term investment in agriculture. While these studies examine the correlates and effects of insurgencies, our study is the first to investigate the effects of a counterinsurgency policy in India.

The rest of the paper is organized as follows. Section 2 provides a discussion of related literature, Section 3 outlines a theoretical framework and Section 4 provides a brief history of the Naxalite movement in India and the Greyhounds. Section 5 provides an overview of the synthetic control method of analysis and the data. Section 6 describes the results while Section 7 discusses the findings. Section 8 concludes.

2. Literature review

Fig. 1 provides a framework, derived from Brück et al. (2011), to assess the dynamic three-way relationship between insurgency, counter-insurgency and economic outcomes which we discuss in this section. As the negative relationship between insurgency and economic outcomes is well established in the literature (for example see Blattman and Miguel, 2010), we focus this review on the part of the literature that analyzes the effects of counterinsurgency policies.

The first part of the literature examines the state response to insurgencies in terms of the effects on violence. Insurgencies depend on active support of the civilian population. The "hearts and minds" mechanism posits that by providing the population with better public services, the government can change perceptions of the population towards the government. Civilians would then be less likely to support the insurgency and more likely to supply information to counterinsurgents regarding the whereabouts of

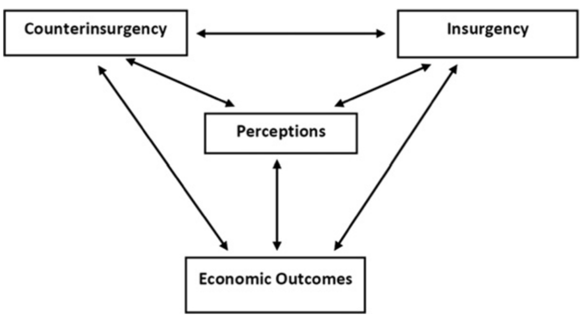


Fig. 1. Insurgency, counterinsurgency, perceptions and economic outcomes.

insurgents. Exploiting spatial variation in service provision through the Commanders Emergency Reconstruction Program (CERP) in Iraq. Berman et al. (2011b) find evidence in support of this theory. However, Beath et al. (2011) find that while the National Solidarity Program (NSP) in Afghanistan improved villagers' perceptions of the government, it had no effect on violence level. A related "opportunity cost" approach to counterinsurgency postulates that improved economic environment, labor market conditions, etc. increase the costs of participating in the insurgency thereby reducing the supply of insurgents (Berman et al., 2011a). Similarly, more coercive counterinsurgency policies (such as drone attacks) could either deter civilian support and reduce the effectiveness of insurgents or drum up support for the insurgents, primarily by inflicting "collateral damage" on civilians (Johnston and Sarbahi, 2016; Kocher et al., 2011).

A second strand of literature focuses on the use of economic indicators to assess the effectiveness of counterinsurgency policies. Conflicts can negatively affect economic activity both directly (for example, destruction of human and physical capital) and indirectly by generating political instability and uncertainty about future policies and outcomes, which negatively affects incentives to save and invest in the economy (Aisen and Veiga, 2013; Brück et al., 2011; Singh, 2013). Counterinsurgency polices, by reducing uncertainties and boosting confidence of civilians may enhance investment and economic activity.[1]

Before making investments, individuals and firms try to assess the probability of being affected by conflict and these perceptions are vulnerable to actions of the state and the insurgents. Under the cumulative-prospect theory paradigm, over-weighting of the probability of terrorist activities can lead to sub-optimal level of investment and output in the economy. In such a scenario, Naor (2015) theoretically shows that an efficient government can produce a security good (financed through taxes) to prevent such production losses. This in turn may further lead to a virtuous circle: increased counterinsurgency effort by the government would attract more investment and once investments increase there is further incentive for the government to maintain its security policy in order to protect its tax base. Berman et al. (2013), using data from the Philippines show that holding other things constant, investment increases with counterinsurgency effort of the government, if the taxation rate (of the government) is less than the rate of extortion (by insurgents).

Bearing this relationship in mind, this strand of the literature has examined the reduced form relationship between security policies and economic outcomes to assess the effectiveness of such policies. An early example of this method is the use of exchange rates to evaluate the effectiveness of U.N. peacekeeping intervention in Lebanon (Sobel, 1998). Zussman and Zussman (2006) find that the Israeli and Palestinian stock markets responded negatively to Israel's assassinations of senior political leaders of Palestinian terrorist organizations but positively to the assassination of senior military leaders. Similarly, Coyne et al. (2010) find the value of long-term financial assets to be good indicators of credible peace processes during the civil war in Sri Lanka. More recently, there has been a spate of papers analyzing counterinsurgency policies in Iraq: Chaney (2008) finds evidence that the Iraqi bond market fell following the news of coalition troops withdrawal but responded positively to news of negotiations with Iran, while various economic and financial outcomes indicate that the "Surge" had limited effect in stabilizing Iraq (Amara, 2012; Greenstone, 2007). This literature is summarized in Table 1. Not only do we contribute to this literature by analyzing an example from India, but we also make a methodological contribution by showing how the synthetic control methodology can be applied to study such policies.

3. Conceptual framework

In this section we outline a simple growth model accounting for insecurity, to motivate the empirical analysis that follows in the remainder of the paper. Consider an economy consisting of infinitely identical firms and households.[2] The representative firm maximizes expected profits (Eq. (1)) subject to a production technology constraint (Eq. (2)):

$$\text{Max}: E\pi = h(Y, K, \beta, r, \delta) \tag{1}$$

$$\text{s.t. } Y = f(K, A) \tag{2}$$

where Y is the output, K is the capital input (can be both physical and human capital) and A is a technology parameter. Conflicts can negatively affect economic activity both directly (for example, the firm might have to pay "taxes" to insurgents, face destruction of property, etc.) and indirectly by generating political instability (for example, strikes) implying that the firm may not receive the full output Y. This uncertainty in the security environment is captured in the expected profits of the firm by the parameter $\beta = \beta(p, \lambda)$ which includes both the probability, p, that the firm faces a loss due to conflict, and the fraction of output, λ, that the firm loses when exposed to conflict, where $p, \lambda \in [0, 1]$. The price of capital is given by r (price of the output is normalized to one) and δ is the rate of depreciation of capital.

Similarly, the representative household chooses an intertemporal path of consumption to maximize lifetime utility U (Eq. (3)) subject to the intertemporal budget constraint (Eq. (4)):

$$\text{Max}: U = U(c, \mu, \rho, \theta) \tag{3}$$

[1] Counterinsurgency policies may also lower long term economic growth by adversely affecting the quality of political institutions (Aguirre, 2016).

[2] See Carmignani (2003) for a broader discussion of the theoretical relationship between political instability and macroeconomic outcomes.

Table 1
Counterinsurgency and economic outcomes.

Source	Context	Outcomes	Results
Sobel (1998)	U.N. peacekeeping intervention in Lebanon, 1973–1984	Lebanese exchange rate	A substantial long-run appreciation of the Lebanese Pound indicates that the U.N. peacekeeping forces was effective in stabilizing the state
Zussman and Zussman (2006)	Israel's assassinations policy, 2000–2004	Tel Aviv 25 index	The market declines following Israel's assassinations of senior political leaders in Palestinian terrorist organizations but increases following assassinations of senior military leaders
Coyne et al. (2010)	Sri Lankan civil conflict, 1997–2008	All Share Price Index (ASPI), Colombo Stock Exchange	Long-term financial asset prices were an accurate indicator of the sustainability of peace agreements between the LTTE and the Sri Lankan government
Amara (2012)	Iraq conflict, 2003–2011	Iraqi exchange rate; treasury bill differential rates between the US and Iraq bills; crude oil production; electricity generation	None of the economic variables provide compelling evidence that the “surge” helped stabilize the Iraqi state.
Greenstone (2007)	Iraq conflict, 2003–2007	Iraqi bond market prices; crude oil production	Bond prices fell following the military “surge” in Iraq indicating that the intervention was not effective. Crude oil production showed no change
Chaney (2008)	Iraq conflict, 2006	Iraqi bond market prices	Iraqi bond market fell following the news of a possible withdrawal of coalition troops but responded positively to news of negotiations with Iran
Berman et al. (2013)	Various insurgencies in the Philippines, 2002–2008	Value of industrial building permits per capita	Government counterinsurgency efforts positively associated with investment

$$\text{s.t. } \dot{a} = (r-\mu)a-c \tag{4}$$

where the theoretical framework assumes: (i) that households live infinitely, (ii) household population grows at the rate μ, and (iii) assets can be held as either capital or loans (both are perfect substitutes, providing the same rate of return, r). Per capita consumption and assets are represented by c and a respectively. The utility function also depends on the rate of time preference (ρ) and a preference parameter (θ), where $\theta, \rho > 0$. The solutions to the maximization problem of the firm and the household respectively are:

$$r^* = q(f'(K), \delta, \beta) \tag{5}$$

$$g^* = z(r^*, \rho, \theta) \tag{6}$$

where g^* is the steady state growth rate of per capita consumption (and for capital and output). Further substituting Eq. (5) in (6) we have:

$$g^* = z(f'(K), \delta, \beta, \rho, \theta) \tag{7}$$

The Euler equation above deviates from the standard steady state growth rate equation due to the presence of the insecurity term β. The greater the amount of insecurity in the economy (a higher p and/or λ), the lower is the rate of accumulation of assets and growth. This framework can be extended to incorporate the cumulative-prospect theory paradigm to show that even at low levels of conflict, the self-assessed probability of suffering a loss from the insurgency, p, could be sufficiently high to result in substantial loss of output (Naor, 2015).

Now assume that the government undertakes a counterinsurgency policy. A counterinsurgency policy could improve security by reducing the amount of output lost due to conflict (λ). Further, it could also improve perceptions of the security environment thereby reducing the perceived probability of facing conflict (p). This implies that β can be expressed as a function of the counterinsurgency policy (τ), where $\beta'(\tau)<0$ and $\beta''(\tau)>0$. Given the negative effect of insecurity (β) on growth, this in turn implies that an effective counterinsurgency policy should increase incentives for investment and hence output. Thus, analyzing the reduced form relationship between security policies and economic outcomes can be used to test the effectiveness of such policies. The empirical counterpart of our hypothesis can be written in the following way:

$$Y = \alpha + \gamma T + \epsilon \tag{8}$$

where T represents the counterinsurgency policy. Given the abovementioned conceptual framework, we expect γ to be positive and significant, implying that the policy is effective. Section 5 describes the estimation strategy that formally tests this hypothesis.

4. The Naxalite movement

The Naxalite movement traces its roots to Naxalbari, a small village in West Bengal where a tribal farmer was attacked by local landlords over a land dispute in 1967. An armed uprising followed, led by revolutionaries of the Communist Party of India (Marxist), across several states of India with the primary objective of overthrowing the state and establishing a communist regime. Faced with a brutal response by the security forces and riven by internal conflicts, the movement splintered into various subgroups. One of the most prominent violent factions of the Naxalite insurgency, the Communist Party of India (Marxist-Leninist) People's War (more generally known as the People's War Group or PWG), was formed in AP in 1980. Through the 1980s and 1990s the various factions rapidly consolidated their bases, actively engaged the state security forces but showed little intergroup coordination. Of late, however, there have been many mergers – the biggest resulting in the formation of the Communist Part of India – Maoist (CPI-Maoist) in 2004.[3]

Given the nature of the insurgency and the limited amount of information divulged by the government, the exact strength of the Naxalites or the extent of violence (as measured by the number of casualties) are difficult to pin down for the study period. Recent intelligence reports estimate the Naxalites to have about 20,000 armed fighters making it almost twice the size of FARC in Colombia (van Dongen and Reichert, 2011) and to be responsible for about 12,000 deaths over the period 1993–2013 (Indian Express, 2014).

The Naxalite insurgency has imposed economic costs on the affected states through various channels. In addition to the human casualties, Naxalites impose direct costs on the economy by destroying public infrastructure – such as government buildings, railway stations, railway lines, telephone exchanges and burning state transportation buses (for examples see Singh, 1995). Further, in some areas the Naxalites run a “parallel” administration making property rights insecure and holding up development activity (Ahmed, 1993).[4] Additionally reports from the field indicate that civilians caught between the insurgents and the government forces face reduced access to health care (Solberg, 2008) and educational services (Human Rights Watch, 2009).

The Naxalites also impede economic growth by administering a “kidnap and extortion empire” in their areas of operation. Extortion from small and large enterprises as well as individuals is reportedly common in areas under Naxalite control (Srinivasan, 1997; Das, 2000). Examples include “taxes” ranging from Rs. 100 to Rs. 1000 per household (Ninan and Ahmed, 1987), and Rs. 100–1000 annual fees to own vehicles (Mishra, 2002). Closest to our study period, meticulously maintained accounts obtained by the police show that the total revenue of the Naxalites in one region of AP was Rs. 62 mn. over the period 2001–2003 (Ramana, 2014).

The value of public and private property destroyed by the Naxalites and the money collected through extortion is an underestimate of the true cost of the conflict as it does not account for the costs of insecurity. Firms faced with the risk of conflict may *ex-ante* avoid profitable investments in order to mitigate possible ex-post losses (Singh, 2013; Bundervoet, 2009). In particular, investments that involve sunk costs or those that are more susceptible to violence may not be undertaken leading to the economy to operate at a sub-optimal level. Note that as opposed to a smaller fraction of the population that actually experiences violence, the costs stemming from insecurity relate to larger sections of society.[5]

4.1. State response and the Greyhounds

The state counterinsurgency response to the rapid growth of the Naxalite movement since the 1980s has been lacking and inconsistent. The affected states have primarily relied on the regular police force to maintain security, with virtually no success. Further, since maintaining law and order in India is the responsibility of the states, until recently, there has been little coordination between the central and the state governments. The role of the central government has been largely restricted to providing reinforcements from the central police organizations when requested to do so. The deployment of central police forces is usually for limited time periods and have done little to boost counterinsurgency efforts (Oetken et al., 2009; Ramana, 2009).

Of the affected states only AP raised a separate police force, called the Greyhounds, whose main purpose was to combat the Naxalite insurgency in the state.[6] Established in 1989 as a separate administrative unit, the Greyhounds are an elite commando force specially trained in counterinsurgency methods, well-equipped and have their own intelligence network and other support units. Although exact numbers are not publicly available, the size of the Greyhounds is reported to have steadily increased from 886 in 1989 (Shatrugna, 1989) to around 2000 in 2009 (Priyadershi, 2009).

The introduction of the Greyhounds was also accompanied by a surrender and rehabilitation policy for the Naxalites in AP in 1989 and later followed by a ban on all Naxalite affiliated groups in 1993 (Ramana, 2009). There was, therefore, an overall change

[3] A more detailed description of the history of the movement can be found in the online appendix.

[4] Following the delicensing of media and an increased interest in the insurgency, reports of such incidents are more readily available post-2000. For example, see the South Asia Terrorism Portal (SATP) for reports of Naxalite activity from popular Indian newspapers. For discussions on incidents pre-2000 see Singh (1995), Louis (2002), and Banerjee (1984).

[5] Rockmore (2016) distinguishes between costs arising from risk of violence and those from the realization of violence in the context of Northern Uganda and finds the former to matter more at the aggregate level.

[6] Other stated responsibilities of the Greyhounds include providing assistance during natural disasters and other grave law and order situations. For more details see the Greyhounds webpage at www.apstatepolice.org.

in the approach towards the Naxalites and we do not disentangle the effects of the various policies. We focus on the Greyhounds, as it was the most crucial (and unique) component of the anti-Naxalite approach taken by AP during this period. Nonetheless, throughout this paper the estimation of the effect of the establishment of the Greyhounds is effectively an estimation of this change in the engagement with the Naxalites in AP.

While we do not have quantitative evidence on the effect of the Greyhounds on Naxalite violence, anecdotal evidence indicates that the initial period (1990–1992) was particularly violent (Ahmed, 1993).[7] Further reports from the latter half of the 1990s suggest that counterinsurgency efforts of the Greyhounds such as infiltration and enhanced information networks were severely affecting Naxalite activities in AP (Reddy, 1998).[8] Reports also suggest that the surrender and rehabilitation policy policy complemented the coercive policy well, encouraging many low-rung Naxalites to surrender in the face of sustained pressure from the police (Ramana, 2009).

This success has led to the Greyhounds training police forces of other affected states such as Maharashtra and Madhya Pradesh and Nepal since 2000 and prompted the Prime Minister of India to suggest that other states raise similar forces.[9]

4.2. The Greyhounds and identification

In this section we discuss changes in the economic and political scenario in AP around the time of the introduction of the Greyhounds. The objective is to rule out concerns regarding the exogeneity of the Greyhounds and any other confounding factors that could have altered the growth of AP.

When assessing the plausibility of the economic effects of the Greyhounds it is important to keep in mind the economic environment of AP. Specifically, are there any other contemporaneous economic policies, not controlled for in the empirical analysis, that could be driving the effects? First, state specific labor laws have been shown to be important determinants of industrial output and in their analysis, Besley and Burgess (2004) find that among 16 major Indian states considered, AP had the most pro-employer labor laws. To allow for this, we control for the Besley and Burgess Labor Reform Index (hereafter, Labor Reform Index) in the analysis.

Second, India embarked on a series of reforms in 1991, a few years after the introduction of the Greyhounds, that included industrial delicensing, relaxation on FDI restrictions and a reduction in tariffs. While these changes are accounted for by the year fixed effects in the state level analysis, we control for these policies using the Aghion et al. (2008) measures of delisencing, FDI restrictions and tariff rates in the industry level regressions. Furthermore, following Aghion et al. (2008) we allow these policies to have heterogeneous effects across states by interacting them with the Labor Reform Index.

Third, towards the end of our study period AP undertook a series of economic and structural reforms under the World Bank's “AP Economic Restructuring Project” and later under “AP Vision 2020” (GoAP, 1999). Note that while these may confound the synthetic control results towards the end of the study period, the regression analyses terminates by 1997. Since the results from the two methodologies are quite similar we can rule out the possibility of these policies having a substantial effect on our estimates.

Table A7 in the online appendix shows a timeline of the major political and Naxalite related events in AP during 1980–2000. The Telugu Desam Party (TDP) and the Indian National Congress (INC) were the main contenders for political power in AP during this time period. The TDP government that came to power in 1983 hardened its approach towards the Naxalites over time resulting in the introduction of the Greyhounds in June 1989. The TDP lost the elections to the INC in December 1989 but the new government did not reverse the Greyhounds policy (in fact, it also imposed an official ban on all Naxalite affiliated groups in 1993). Nonetheless, it is possible that the political party in power could have affected the growth pattern of AP through economic or security policies. In order to control for this we have included dummy variables that capture the political identity of the state government in the regression analyses.[10]

Lastly, even though the Greyhounds were officially introduced in 1989, the decision to raise the Greyhounds was announced on June 6, 1988 (Balagopal, 1988). Although, as shown in the results later, this could have led to an announcement effect, we take 1989 as the treatment year because in addition to the introduction of the Greyhounds, there was the important transformation of the counterinsurgency capabilities of the AP Police setup that occurred only after 1989.

5. Research methodology and data

A common problem in the study of macro policy interventions is that a regression approach is usually less appropriate due to the lack of a sufficient number of treated and control units for robust inference. The synthetic control methodology is useful in circumstances such as those of the present study where the event of interest – the creation of the Greyhounds in 1989 – occurred

[7] Janyala (2011) reports 584 deaths in AP during this period. Note that this could in part be also due to an increase in the sophistication and lethality of weapons used by the Naxalites such as AK-47s and land mines (Mitta and Desai, 1996).

[8] The effectiveness of the police in gathering information is further substantiated by a wave of brutal reprisals against suspected informers and infiltrators (Reddy, 2001).

[9] “[…] I believe that given the unique nature of this problem, it is time to have a dedicated force just to tackle naxalism. Affected states must set up Special Task Forces on the Andhra Pradesh pattern and the Centre will provide assistance for this purpose.” PM's Closing Remarks at the Chief Ministers' Conference on Internal Security, New Delhi 2007. Full text of this speech is available at http://pmindia.nic.in/speech-details.php?nodeid=613 (accessed June 1, 2012).

[10] Further, the introduction of the Greyhounds is reported to be an idea of K.S. Vyas, an officer with Indian Police Service, posted in AP (Raju, 2010). The allocation of an officer to a particular state is done by the central government on the basis of merit and other exogenous factors. K.S. Vyas was later assassinated by the Naxalites in 1993.

at an aggregate level (state level) and affected aggregate entities (states of India).[11] More importantly, as further elaborated below, the synthetic control approach can be motivated as a generalization of the linear panel difference-in-differences model where the unobserved individual specific confounders are allowed to vary with time, thereby relaxing the assumption of a similar difference between the treated and the control in the absence of treatment. However, other assumptions of the difference-in-differences model continue to hold – the synthetic control methodology precludes the possibility of an announcement effect and spillovers between the treated and controls (these limitations are examined in detail in Section 7). Although this approach does not allow for inference through traditional asymptotic methods, informative inference is still possible through falsification (placebo) tests.

We now summarize the synthetic control methodology of Abadie and Gardeazabal (2003) and Abadie et al. (2010) (AG and ADH hereafter, respectively; notation and equations are those of ADH). Suppose we have $J+1$ regions with the first region exposed to the treatment and the remaining J regions being the potential controls. There are T time periods and T_0 pre-intervention time periods such that $1<T_0<T$. Let Y_{it}^N be the outcome observed for region $i\in\{1,\ldots,J+1\}$ if it is not exposed to the treatment and Y_{it}^I be the outcome observed for the ith region if it is exposed to the treatment in time periods T_{0+1} to T. Let D_{it} be a dummy variable that takes the value of 1 if region i is exposed to the treatment at time period t and 0 otherwise, i.e.

$$D_{it} = \begin{cases} 1 & \text{if } i=1 \quad \text{and} \quad t>T_0 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

The observed outcome for region i at time t is then

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it} \tag{10}$$

where $\alpha_{it} = Y_{it}^I - Y_{it}^N$ is the effect of the treatment on region i at time t. We are interested in estimating $(\alpha_{1,T_{0+1}},\ldots,\alpha_{1,T})$. Since we observe Y_{it}^I, in order to estimate α_{it} we just need to estimate Y_{it}^N. Let Y_{it}^N be given by a generalized difference-in-difference (fixed effects) model, where the unobserved individual specific effect is allowed to vary with time

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \epsilon_{it} \tag{11}$$

Here, Z_i is a vector of observed covariates (which may contain time varying covariates), μ_i are individual specific unobserved confounders, λ_t is a vector of unobserved common factors and ϵ_{it} are mean 0 shocks. Let $W=\{w_j\}_{j=2}^{J+1}$ be a set of non-negative weights that sum up to one. Each such set of weights represents a particular weighted average of controls, i.e. a particular synthetic control. Let there be weights $(w_2^*,\ldots,w_{J+1}^*)$ such that

$$Z_1 = \sum_{j=2}^{J+1} w_j^* Z_j \quad \text{and} \quad Y_{1t} = \sum_{j=2}^{J+1} w_j^* Y_{jt} \quad \forall t\in\{1,\ldots,T_0\} \tag{12}$$

i.e. (i) the weighted average of the covariates of the controls perfectly replicates the covariates of the treated unit and (ii) the weighted average of the pre-treatment outcomes of the controls perfectly matches the pre-treatment outcomes of the treated unit. Then, ADH show that if $\sum_{t=1}^{T_0}\lambda\prime_t\lambda_t$ is non-singular, we have

$$Y_{1t}^N - \sum_{j=2}^{J+1} w_j^* Y_{jt} = \sum_{j=2}^{J+1} w_j^* \sum_{s=1}^{T_0} \lambda_t \left(\sum_{n+1}^{T_0} \lambda\prime_n \lambda_n \right)^{-1} \lambda_s\prime(\epsilon_{js} - \epsilon_{1s}) - \sum_{j=2}^{J+1} w_j^* (\epsilon_{jt} - \epsilon_{1t}) \tag{13}$$

Further, they show that the mean of the right hand side of Eq. (13) is close to zero "… if the number of pre-intervention periods is large relative to the scale of the transitory shocks" (ADH, p. 495). We can therefore estimate the impact of the treatment as

$$\alpha_{it} = Y_{it} - \sum_{j=2}^{J+1} w_j^* Y_{jt}^N \quad \forall t\in\{T_{0+1},\ldots,T\} \tag{14}$$

Usually we are unable to get a perfect synthetic control because weights do not exist such that the equations in (12) hold exactly. The weights are then selected such that the equations in (12) hold approximately. Note that by not restricting λ_t to be constant over time, the synthetic control methodology relaxes the traditional difference-in-difference assumption that in absence of treatment, the difference between "treatment" and "control" groups is constant over time.

In order to implement the synthetic control methodology, let X_1 be the vector of Z_1 and pre-treatment outcomes for the treated state and X_0 be the matrix of Z_j and pre-treatment outcomes for the J control states. The vector of weights W^* is chosen to

[11] For some applications of this methodology see Lee (2011) and Billmeier and Nannicini (2013).

minimize $(X_1 - X_0 W)' V (X_1 - X_0 W)$ subject to the weights $\{w_j\}_{j=2}^{J+1}$ being non-negative and summing up to 1. The weighting matrix V can be any positive definite matrix but note that the choice of V affects W^*. Following the existing literature, we allow the choice of V to be data driven, by choosing V such that the mean square error of the outcome variable is minimized for the pre-treatment period. All calculations in this paper were performed using the software SYNTH for STATA, developed by ADH.

Given the small number of control units, asymptotic inferential techniques cannot be applied to comparative case studies. To estimate the credibility of the results in this study, we conduct placebo tests similar to those in AG and ADH where the entire analysis is performed for a control state as if the control state was treated. Since the control state was not treated, we should not expect to find any treatment effect. If the placebo studies using control states iteratively assigned to treatment status create treatment effects of magnitude similar to the ones estimated for the actually treated state, then the conclusion is that the analysis does not provide any convincing evidence of a (true) treatment effect.

Although we primarily use the synthetic control methodology, difference-in-difference regressions are also provided whenever possible. In all these regressions the standard errors are clustered at the state level in order to mitigate concerns regarding serial correlation.[12]

The primary economic indicator used to measure the effectiveness of the Greyhounds in real per capita net state domestic product (pcNSDP). We further investigate the channels through which the treatment affects pcNSDP using components of pcNSDP such as industry, manufacturing and registered and unregistered manufacturing.[13] All these outcome measures are measured in 1999 prices.

We use standard predictors of economic growth such as Human Development Index (HDI), population density, road density, percentage of households with access to safe drinking water, per capita electricity consumption, per capita development expenditure and percentage of population below the poverty line. We also use some observed covariates (Z_i) specifically for certain outcomes. For example, for the industrial sector and its various subsectors the Labor Reform Index is used to proxy the industrial labor relations in the state.[14] The X_0 and X_1 matrices consist of a combination of observed covariates (averaged over the entire pre-intervention period) and some pre-treatment values of the outcome of interest.[15] The full list of the variables and details regarding their sources are provided in the online appendix A1.

Finally, the period under consideration in this study is 1970–2000 which gives us 1970–1988 as the pre-treatment period and 1989–2000 as the treatment period.[16] The treated unit is AP, and the potential control units are the other Naxalite affected states: Bihar, Madhya Pradesh, Maharashtra, Karnataka, Orissa, Uttar Pradesh and West Bengal.[17]

6. Results

6.1. Main result

We begin our analysis with the effects of the creation of the Greyhounds on the pcNSDP of AP. Fig. 2(a) plots the trajectories of pcNSDP of AP and a simple average of the pcNSDP of the control states over the period 1970–2000. The equally weighted average pcNSDP for the control states lies above that of AP for most of the pre-treatment period and well below that of AP in the treatment period. This divergence in pcNSDP after 1989 however, is not the true treatment effect since before the formation of the Greyhounds force, AP was a consistent underperformer relative to the rest of the Naxalite affected states. As an equally weighted average of the rest of the Naxalite affected states was significantly different from AP in the pre-treatment period, using it as a comparison group for AP would be inappropriate.

The synthetic AP is constructed as a weighted average of the states in the potential control group that most closely resemble AP in terms of (i) pre-treatment values of pcNSDP and (ii) pre-treatment values of pcNSDP growth predictors. Table 2 compares the pre-treatment characteristics of AP to those of the synthetic control (appropriately weighted average of controls) and also to the simple average of controls. As can be seen from the table, the synthetic control matches actual AP in terms of HDI, population density, road density, percentage of urban households with access to safe drinking water and per capita electricity consumption far more closely than the simple average of the control states. Similarly, the synthetic control is fairly close to actual AP in terms of pre-treatment pcNSDP.

[12] Admittedly this results in 8 clusters, possibly biasing the standard errors downwards (see Angrist and Pischke, 2008).

[13] A analysis of the services and agricultural sector is available in the online appendices A4 and A5.

[14] The states are allowed to amend the central government's Industrial Disputes Act of 1947. So even though all states had the same starting point, currently labor market regulations differ across states. Besley and Burgess (2004) code each state amendment as pro-worker (+1), neutral (0) and pro-employer (−1) and calculate the net direction of change for each year over the period 1947–1997. The index is arrived at by cumulating the scores over time. See Besley and Burgess (2004) for further details.

[15] While the existing literature does not specify a limit on number of pre-intervention covariates to use for matching (personal communication with Alberto Abadie), adding more variables can to lead to the standard problem of dimensionality. Although we have a fairly rich set of covariates, we restrict the total number of variables to eight and use the remaining covariates in other specifications as robustness checks.

[16] While the Naxalite insurgency started in 1967, we take 1970 as the start year as it is the earliest year from which we have consistent information available.

[17] The states of Chhattisgarh, Uttaranchal and Jharkhand were carved out of Madhya Pradesh, Uttar Pradesh and Bihar respectively in Nov. 2000. Our analysis takes into account the undivided states of Madhya Pradesh, Uttar Pradesh and Bihar. A map of India with the Naxalite affected states is provided in the online appendix (Fig. A7).

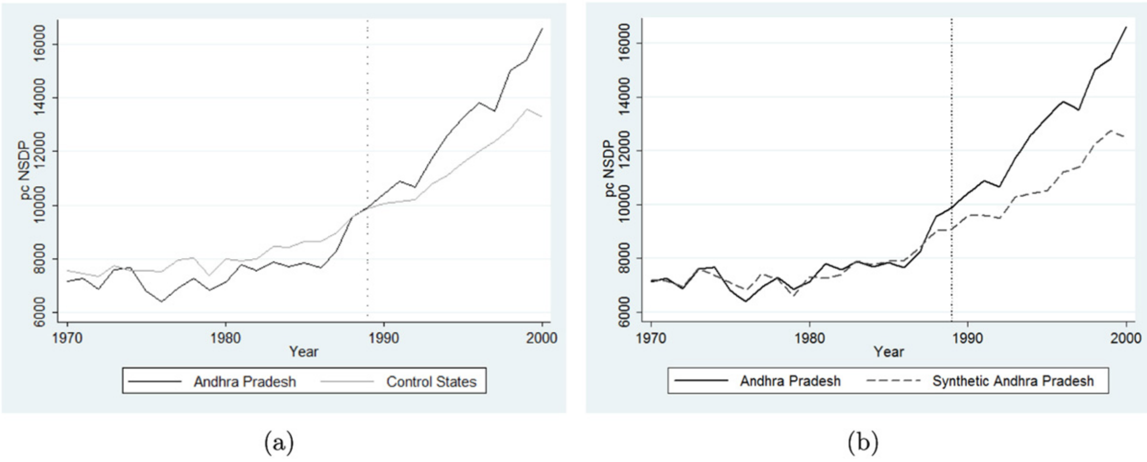


Fig. 2. Trends in pcNSDP (Panel (a) shows an equally weighted average of the controls and Panel (b) shows the synthetic control).

Table 2
pcNSDP predictor means.

Variables	Andhra Pradesh	Synthetic control	Control states		
			Mean	Min	Max
HDI	0.30	0.28	0.29	0.24	0.36
Population density (persons/sq. km.)	176.50	180.46	303.86	106	588.5
Urban HH with safe drinking water (%)	63.27	68.21	70.90	51.33	85.56
Per capita electricity consumption (KwH)	114.35	122.86	132.44	88.84	239.28
Road density (km/1000 sq km area)	366.00	405.99	487.14	202	620.5
1973 pcNSDP (1999 prices)	7605.60	7634.94	7728.50	4937.43	9553.13
1983 pcNSDP (1999 prices)	7891.15	7899.00	8478.88	5084.04	11,848.05
1984 pcNSDP (1999 prices)	7703.05	7759.85	8424.71	5556.31	11,686.64

Table 3 shows the weights given to each state in the control group when constructing the synthetic AP. The optimal weights are positive for Bihar, Karnataka, Madhya Pradesh and Orissa; and zero for the other states. Of the four states that border AP (Karnataka, Madhya Pradesh, Orissa, and Maharashtra), three (Karnataka, Madhya Pradesh and Orissa) account for over 80% of the weight. This gives us further confidence in our estimates as these neighboring states are more like AP in unobserved variables like geography and culture relative to the other controls.

Fig. 2(b) plots the trajectory of pcNSDP of AP and the synthetic control for the period 1970–2000. In the pre-treatment period 1970–1988, the synthetic control behaves very similarly to that of AP till 1987. In the treatment period, the pcNSDP of the synthetic control diverges from that of AP, with the gap increasing steadily till the end of the study period. As the evolution of pcNSDP for the synthetic control is what the evolution of pcNSDP would have been for AP if it had not raised the Greyhounds force, the gap between AP and its synthetic control is an estimate of the treatment effect. Lastly note that the divergence starts a year before in 1988, possibly indicating an announcement effect discussed in Section 4.2.

The effect can be quantified in terms of percentage average gain – the average yearly gap between pcNSDP of AP and that of the synthetic control expressed as a percentage of the average yearly pcNSDP of AP over the treatment period. The average yearly gap between AP and that of the synthetic control was Rs. 2065.2 and the average yearly pcNSDP of AP was Rs. 12,820 during the

Table 3
State weights: pcNSDP.

State	Weight
Bihar	0.19
Karnataka	0.34
Madhya Pradesh	0.42
Maharashtra	0.00
Orissa	0.05
Uttar Pradesh	0.00
West Bengal	0.00

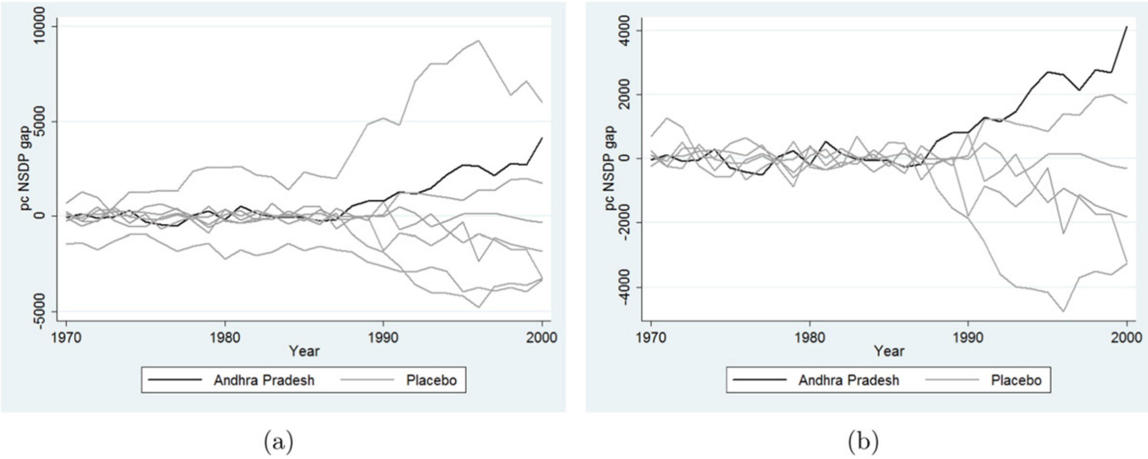


Fig. 3. pcNSDP gap in Andhra Pradesh and placebo gaps of control states (Panel (a) has all controls and Panel (b) discards states with pre-treatment MSPE two times higher than Andhra Pradesh).

treatment period. AP consequently experienced a percentage average gain of 16.11% of its pcNSDP during this period. Another way to view the benefits is in terms of the change of growth rates. The synthetic control had an annual growth rate of 2.68% over the period 1989–2000 while AP grew at an annual rate of 4.41%.[18] While at first these figures might seem surprisingly large note that (i) the immediate effect is small (8.8% gap in 1989), increases steadily over time and becomes markedly large in magnitude only by the end of the study period; (ii) these estimates capture an *upper bound* of the actual effect (discussed further in Section 7.2); and (iii) the estimated effects are in fact comparable to those for some other state level policy changes (for example, changes in industrial labor regulations analyzed, Besley and Burgess, 2004).[19,20]

We evaluate the validity of our results by conducting a series of placebo tests that involve iteratively applying the synthetic control method to each of the seven control states. Fig. 3(a) shows pcNSDP gap in AP and the placebo gaps for all the control states. The estimated pcNSDP gap between each control state and its synthetic counterpart is represented by the gray lines. The black line represents the estimated pcNSDP gap between the AP and its synthetic counterpart. It is clear from Fig. 3(a) that the estimated pcNSDP gap for AP States is large (positive) in comparison to the distribution of pcNSDP gaps for the control states. The pre-treatment root mean squared prediction error (RMSPE)[21] for AP is just 273.48, while the median pre-treatment RMSPE for control states in the placebo runs is just 377.97, indicating relatively good pre-treatment fits. However, pre-treatment RMSPE for Maharashtra and Bihar are large – 1910.02 and 1616.18, respectively – casting doubt on their reliability (ADH, pg.502). Therefore, in Fig. 3(b), we drop placebo runs for states that give pre-treatment RMSPEs that are at least two times higher than the pre-treatment RMSPE for AP. On dropping the controls with poor pre-treatment fit (Bihar and Maharashtra) the pcNSDP gap for AP is clearly the largest (positive) of all the pcNSDP gaps.

Dropping controls with a poor pre-treatment fit involves some amount of subjectivity. We can also check the credibility of the estimated treatment effect for AP by comparing the post-treatment RMSPE to pre-treatment RMSPE ratios. Since controls with a poor pre-treatment fit are weighted down one no longer needs to drop them. Fig. 4(a) shows that this ratio for AP is larger than that of the controls.[22]

Next, we assess the robustness of our results in three ways. Firstly, we test the sensitivity of the baseline model to the states in the control pool. For this purpose we iteratively drop one of the controls that receive positive weight in the base specification and re-estimate the baseline model.[23] The results of these iterations are shown in Fig. 4(b) where Fig. 2(b) is superimposed with the synthetic controls estimated by iteratively leaving out one of the controls (dashed gray lines). Even though the pool of the control states is relatively small, Fig. 4(b) shows that the results are fairly robust to the exclusion of any given control state.

[18] The maximum gain observed was Rs. 4133.7 at the end of the treatment period. The yearly gains are provided in Table A8 in the online appendix.

[19] These effects are quite meaningful and could have in turn had considerable welfare effects. For example, Bhalotra (2010) estimates the income elasticity of infant mortality to be −0.33 at the state level in India during the same time period (1970–1997). Back of the envelope calculations then indicate that the income gains noted here would be associated with a 5.3% reduction in infant mortality.

[20] A cost-benefit analysis is not possible due to the unavailability of information on the cost of the intervention. However, a recent proposal to raise similar forces in other Naxal affected states indicates the initial setup cost to be 3.36 billion rupees (Indian Express, 2013).

[21] The pre-treatment RMSPE is a measure of the lack of fit between AP and its synthetic control and defined as: $\sqrt{\frac{1}{T_0}\sum_{t=1}^{T_0}\left(Y_{1t}-\sum_{j=2}^{J+1}w_j^*Y_{jt}\right)^2}$. The post-treatment RMSPE and the RMSPE for other states is similarly defined.

[22] Note that this technique is analogous to that of randomized inference. The p-value constructed in this context implies that if treatment were to be assigned at random then the probability of getting a ratio at least as large as that of AP would be 1/8=0.125. While this is not significant at conventional levels (one-tailed test), note that the p-value necessarily hinges on the number of control states. See ADH for a further discussion.

[23] Dropping states that receive zero weight does not change the results of the baseline model.

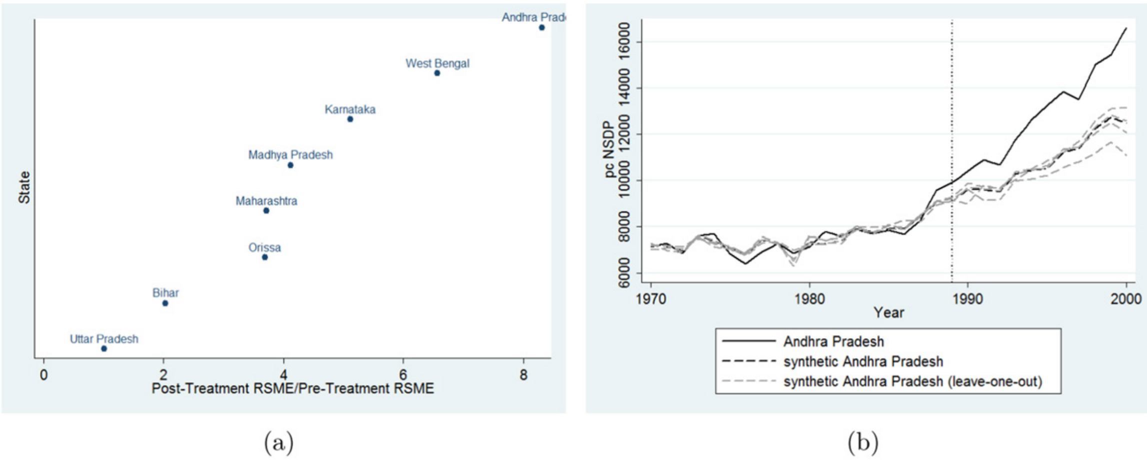


Fig. 4. Validity checks for pcNSDP gap (Panel (a) shows ratios of post-treatment RMSPE to pre-treatment RMSPE and Panel (b) shows the leave-one-out robustness checks).

Secondly, we check the sensitivity of the results by using different combinations of predictors of pcNSDP when constructing the synthetic control. We find that our results remained robust to the use of other variables such as the percentage of rural population below the poverty line, per capita credit utilization, log per capita development expenditure, foodgrain yields, percentage of net sown area irrigated, number of riots per capita, murders per capita, and police per capita instead of percentage of urban households with access to safe drinking water. Similarly, the results are robust to using adult literacy rate or life expectancy at birth instead of HDI or using percentage of villages electrified instead of per capita electricity consumption.

As mentioned earlier, the synthetic control methodology weakens the assumptions of the usual difference-in-difference estimator. As a third robustness check, we also estimated effect of the Greyhounds using the difference-in-difference methodology. Since all covariates are not available for the entire period the regressions are restricted to the period 1970–1997 (i.e. we lose the last three years of our treatment period). These results are presented in Table A1 in the online appendix. In the main specification in column 1 in addition to controlling for state fixed effects, year fixed effects and state-specific time trends, we also control for the Labor Reform Index, the political orientation of the party in power, whether the party was concurrently in power at the center and if the state experienced President's Rule (proxy for political instability). Column 2 further includes controls such as per capita development expenditure, grants to the state from the center and electricity consumption (proxies for the differences in human capital and infrastructure across states). The effect of Greyhounds on pcNSDP is positive and significant in both specifications. While some of these controls are potentially endogenous (and therefore these results should be viewed as suggestive evidence), we find the estimated effects using the synthetic control methodology and the difference-in-difference methodology to be quite similar: using the synthetic control methodology the estimated treatment effect is Rs. 1686.9 over 1970–1997 while using the latter it is Rs. 2037.4 (column 1) and Rs. 1917.9 (column 2).

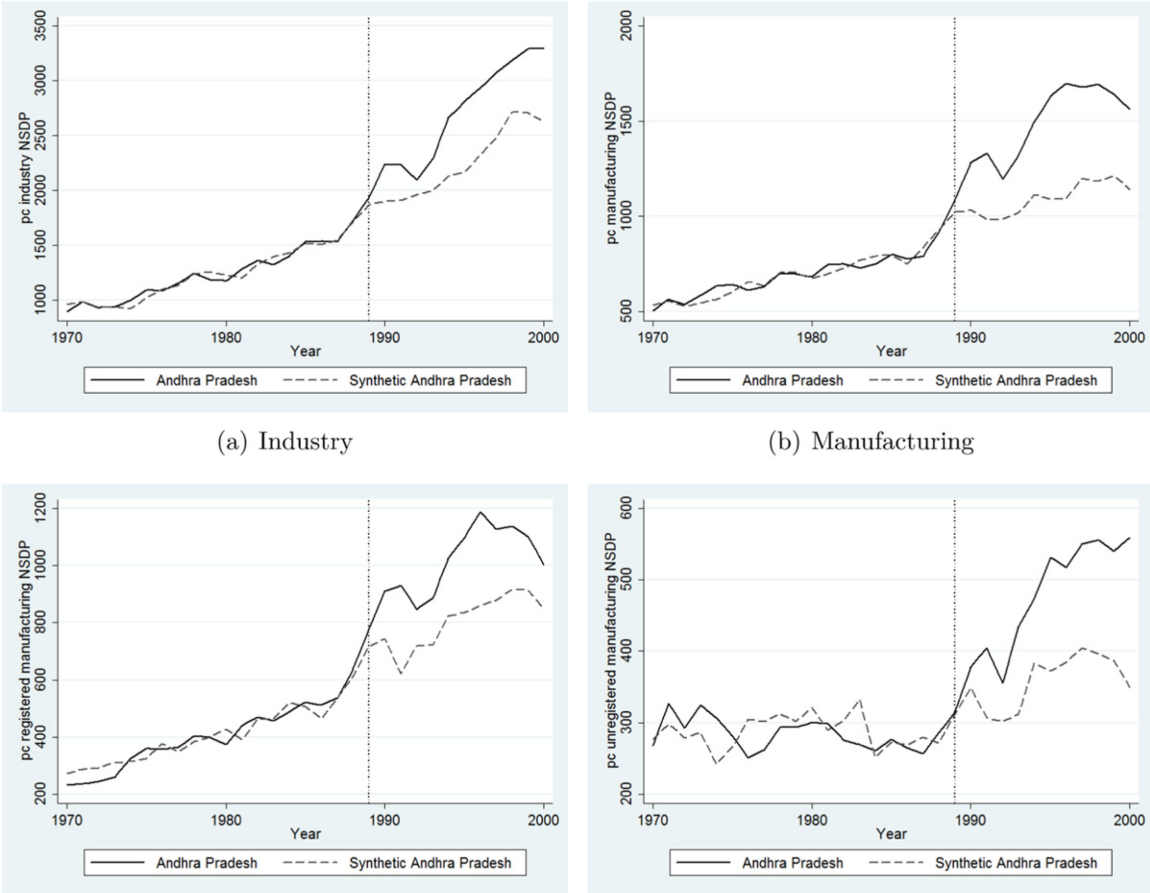
6.2. Sectoral heterogeneity

We explore sectoral heterogeneity by looking at the effects of the Greyhounds on the industrial, services and agricultural sectors. While the industrial sector is analyzed below, a similar analysis of the services and agricultural sectors is reported in Sections A4 and A5 of the online appendix. Within the industrial sector we also analyze the effects on the manufacturing sector and a further breakup of the manufacturing sector into registered and unregistered manufacturing.[24]

Fig. 5(a) displays the trends in industrial outputs of AP and the synthetic control. The synthetic AP almost perfectly replicates the per capita industrial NSDP of AP over the entire pre-treatment period, followed by a marked divergence after the introduction of the Greyhounds indicating a clear positive effect on the industrial output. This gap translates into an average of Rs. 437.95 over the period 1989–2000 or 16.41% of the average industrial output of AP during this period.[25] Similar effects are observed in

[24] The industrial sector consists of mining and quarrying, manufacturing, construction, gas, electricity and water supply. In India registered manufacturing sector consists of all manufacturing firms that employ more than 20 workers without using electricity or more than 10 workers and using electricity.

[25] The average per capita industrial NSDP of AP is Rs. 2668.74 during 1989–2000. The synthetic control grew at an annual growth rate of 2.89% as opposed to the annual growth rate of 4.56% of AP.



(a) Industry (b) Manufacturing

(c) Reg. Manufacturing (d) Unreg. Manufacturing

Fig. 5. Trends in per capita industry output: Andhra Pradesh vs. synthetic control.

Figs. 5(b)–(d) which present the effects of the Greyhounds on the manufacturing, registered manufacturing and unregistered manufacturing respectively.[26]

The similarity of the synthetic control to AP in terms of the pre-treatment characteristics and weights assigned to the controls in constructing the synthetic control are shown in Tables A2 and A3 in the online appendix. On performing placebo tests and comparing the ratio of post-treatment RMSPE to the pre-treatment RMSPE for AP to those for the placebos, we find that these results are credible (Figs. A1–A5 in the online appendix).

Further we find that our results are robust to using different combinations of predictors of industrial output (and its components) and are not sensitive to the composition of the control pool (Fig. A6 in the online appendix).[27] Finally, we also compare the magnitude of the estimates obtained from synthetic control methodology to those from the difference-in-difference regression framework (Tables A4 and A5 in the online appendix). The results show a positive association between Greyhounds and all measures of industrial performance and that the estimates from the synthetic control and difference-in-difference methodologies are fairly similar.

6.3. Sub-sectoral heterogeneity

While the analysis presented so far considers the sectoral aggregates, it is possible that there is variability in the vulnerability of some sub-sectors to Naxalite violence and hence, heterogeneity in the effects of the Greyhounds on a particular sector. We explore this possibility using data on the output of the industrial sub-sectors for the period 1980–2000.

[26] Over the period 1989–2000 the manufacturing, registered manufacturing and unregistered manufacturing sectors in AP (synthetic control) grew at an annual rate of 3.67% (0.92%), 2.13% (1.42%) and 4.91% (0.94%), respectively. The average gaps (percentage average gaps) for the manufacturing, registered manufacturing and unregistered manufacturing sectors are Rs. 377.52 (25.73%), Rs. 202.89 (20.24%) and 112.91 (24.14%) respectively.

[27] The results are robust to the use of other predictors as adult literacy rate, life expectancy at birth, number of mandays lost due to industrial disputes and the membership of labor unions that submit returns in the state, per capita consumption of industrial electricity, percentage of population below the poverty line, road density, per capita credit utilization, number of riots per capita, murders per capita, and police per capita.

Table 4
Impact of Greyhounds on vulnerable sectors: industry sub-sector analysis.

Variable	Real pc sector NSDP
AP* post-1988 dummy* vulnerable sectors	117.3**
	(42.77)
State–year effects	Yes
Sub-sector–year effects	Yes
State-sub-sector effects	Yes
Adjusted R^2	0.509
Observations	576

Notes: Standard errors calculated using robust standard errors clustered at the state level are reported in parentheses. AP stands for Andhra Pradesh and data are for the period 1980–2000. Vulnerable sub-sectors of industry are manufacturing, mining and quarrying and gas, electricity and water supply. Non-vulnerable sub-sector is construction.
* Significant at 10%.
** Significant at 1%.

Recall that the industrial sector consists of four major sub-sectors: mining and quarrying; manufacturing; gas, electricity and water supply and construction. As discussed earlier, the Naxalites depend on their "tax" base to raise funds to fight the government. As firms engaged in mining and quarrying, manufacturing and gas, electricity and water supply are localized, easily identifiable and potential sources of higher revenue, one would expect these sub-sectors to be relatively more vulnerable than construction (an economy wide activity). We exploit this variation in the vulnerability of sub-sectors to use a difference-in-difference-in-difference approach where we compare the difference between vulnerable and non-vulnerable sectors between AP and the other affected states, before and after 1989. The panel regressions take the following form:

$$y_{kst} = \alpha_{ks} + \theta_{st} + \delta_{kt} + \beta(AP * D_{89} * Vul) + \epsilon_{kst} \tag{15}$$

where y_{kst} is the real output of sub-sector k in state s in year t, α_{ks} are state specific sub-sector fixed effects, θ_{st} are state-year fixed effects and δ_{kt} are sub-sector specific year fixed effects. The coefficient of interest (β) is the coefficient on the interaction of a dummy variable for AP (AP), a post-1988 dummy (D_{89}) and the dummy for vulnerable sectors (Vul). Note that the other relevant interaction terms of the triple difference estimation strategy are absorbed by the various fixed effects.

The results presented in Table 4 show that compared to other affected states the Greyhounds led to a significant improvement in the output of the vulnerable sectors after 1989 in AP. Note that it is possible that the introduction of the Greyhounds led to a spillover between sub-sectors within the state, thereby biasing the results. Still, this result does mitigate the concern that the positive effects of the Greyhounds are an artefact of the growth pattern of the states.

7. Discussion

7.1. Mechanisms

While this study identifies economic gains associated with the introduction of the Greyhounds, it does not directly address the issue of the underlying mechanisms through which these changes occurred. Nonetheless, we conjecture that these gains were due to improving perceptions of the security environment in the state of AP during the period 1989–2000. As discussed in Section 2, the hypothesis is that investments and output in the economy would increase as assessments of future security levels improve.

Using disaggregated data we find investment in the manufacturing sector to increase in the presence of the Greyhounds, providing suggestive evidence in favor of this hypothesis. We use the Aghion et al. (2008) state-industry panel data on the registered manufacturing sector collected under the Annual Survey of Industries. The period under consideration in 1980–1997 (nine years pre- and post-treatment) and industrial variables are measured at the two-digit level.[28] We estimate the following regression:

$$y_{ist} = \alpha_{is} + \beta(Grey_{st}) + \theta(X_{ist}) + \delta_{it} + \epsilon_{ist} \tag{16}$$

where y_{ist} is the outcome variable, $Grey_{st}$ is a dummy variable that takes the value of unity from 1989 onwards if the state is AP, X_{ist} are observed covariates, α_{is} are state–industry interactions to control for unobserved time-invariant factors such as location, natural resources, etc., δ_{it} are industry–year interactions that control for unobserved industry–year effects such as changes in technology. The outcome variables considered are logarithms of real output, and three proxies for investment – the number of factories, real physical capital and the number of employees.

[28] The sampling unit in Aghion et al. (2008) is a state and three-digit industry pair. There are on average 64 three-digit industries in each state leading to a considerable amount of heterogeneity in the data. For this paper we aggregate the Aghion et al. (2008) data to the two-digit industry level.

Table 5
Greyhounds and registered manufacturing performance: 1980–1997.

Variable	Log real output	Log no. factories	Log real capital	Log no. employees
Greyhounds	0.221*	0.319***	0.186	0.155*
	(0.108)	(0.0813)	(0.198)	(0.0698)
Labor regulation	−0.0801	0.190	0.229	−0.0193
	(0.204)	(0.120)	(0.178)	(0.147)
Delicense	−0.529	−0.116	−0.100	−0.0218
	(0.469)	(0.195)	(0.454)	(0.423)
FDI reform	0.904	0.328	1.086	0.698
	(0.485)	(0.264)	(0.795)	(0.447)
Log tariff rate	−0.0487	−0.0486	−0.204	0.219
	(0.373)	(0.178)	(0.241)	(0.329)
Delicense* labor regulation	−0.0560*	−0.0531*	−0.00469	−0.0684***
	(0.0274)	(0.0236)	(0.0409)	(0.0186)
FDI reform* labor regulation	−0.0792**	−0.00406	−0.115	−0.0343
	(0.0330)	(0.0223)	(0.0750)	(0.0270)
Log tariff rate* labor regulation	0.0125	−0.0359	−0.0307	0.00684
	(0.0402)	(0.0205)	(0.0369)	(0.0297)
Log education expenditure	0.535*	0.528**	0.658**	0.176
	(0.266)	(0.212)	(0.238)	(0.106)
Log health expenditure	−0.282	−0.158	−0.513**	−0.243
	(0.198)	(0.132)	(0.210)	(0.153)
Log other expenditure	0.508	0.276	0.739	0.363
	(0.336)	(0.217)	(0.440)	(0.210)
Log central grants	−0.373***	−0.0946	−0.280*	−0.243**
	(0.100)	(0.0516)	(0.136)	(0.0703)
Political controls	Yes	Yes	Yes	Yes
Industry–year effects	Yes	Yes	Yes	Yes
State–industry effects	Yes	Yes	Yes	Yes
p-Value of joint test of:				
Labor reg. interactions	0.00	0.07	0.31	0.00
Observations	2639	2639	2639	2639
Adjusted R^2	0.939	0.967	0.913	0.953

Notes: Standard errors calculated using robust standard errors clustered at the state level are reported in parentheses. Political controls include party type, an indicator if the same party is in power in the state and center and President's rule. The details of the variables are provided in the online appendix.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Prompted by an impending balance-of-payments crisis, the Indian economy was liberalized in 1991. Industrial licensing that had been implemented by the central government in order to regulate the manufacturing sector was gradually reversed during the 1980s and virtually removed in 1991. The variable "delicense" indicates the fraction of existing three-digit industries within a two-digit industry that were delisenced. The second component of liberalization policy implemented in 1991, was the relaxation of restrictions on foreign direct investment (FDI). The variable "FDI reform" measures the fraction of existing three-digit industries within a two-digit industry that had any product opened for automatic approval of FDI (up to 51%). The third part of the economic reforms consisted of reductions in tariff rates. The variable "log tariff rate" captures the logarithm of average tariff rate applied at the two-digit industry level. Following Aghion et al. (2008), we also interact the state-level measure of labor regulation with the three policy reform measures in order to capture the differential effects of these policies across states. In addition to this, we also include other covariates such as development expenditure on health education and other services, grants from the center and a variety of political variables. Further details of these data are provided in the online appendix A1.

The results of these regressions are in Table 5. As the results clearly indicate, after controlling for a variety of covariates, the introduction of Greyhounds led to a significant increase in industrial activity – both in terms of output and investments – in AP relative to other Naxalite affected states. The effects are positive and significant for two out of three indicators of investment – number of factories and employees. Other results broadly conform to the existing literature – industries in relatively more pro-employer states benefited more from industrial deregulation (delicensing and FDI).[29]

7.2. Spillovers

Implicit in the calculation of the economic benefits of the Greyhounds is the assumption of no spillover, i.e. outcomes of control units are not affected by the treatment administered to the treated unit. This assumption may be violated in the following

[29] Similar results are found for a specification that includes year dummies instead of industry–year dummies. Results are available in the online appendix.

three ways in the present context. Firstly, there may be a spillover through the security forces. For example, the Greyhounds could offer support to the police forces of other states in the form of training, joint operations, material supply, etc., to tackle the Naxalite insurgency. This would have artificially raised the output of the other Naxalite affected states and thus biased the estimate of the treatment effect downwards. As the Greyhounds started offering training to other Naxalite affected states from 2000 onwards, we terminate the analysis at the year 2000 to avoid this source of bias.

Secondly, spillover between states may happen through civilians migrating to AP for greater security (Libman et al., 2013). This migration may be selective in the sense that the civilians most likely to have the resources to migrate are more productive on average. This could then raise the pcNSDP in AP and lower it in other Naxalite affected states leading to an upward bias in the estimated treatment effect. However, Lusome and Bhagat (2006) report using Indian census data that approximately 80% of the internal migration in India is in the form of intra-district and intra-state migration over the period 1971–2001. Further, in 2001 only 33.7% of the inter-state migration is for employment or business purposes.

Lastly, and most importantly, anti-Naxalite operations by the Greyhounds in AP could result in the movement of Naxalites from AP to the surrounding Naxalite affected states with a less threatening security environment for Naxalites. Anecdotal evidence supports this possibility (for example, Menon, 1993). To the extent that such displaced Naxalites indulged in insurgency activity in their temporary refuge across state borders, the pcNSDP of the other Naxalite affected states would have decreased, resulting in an over estimate of the Greyhounds treatment effect. Unfortunately, there is no publicly available data to check the extent of such bias in the calculated treatment effect. In this case, the calculated treatment effect must therefore be interpreted as an upper bound on the true treatment effect.[30]

7.3. Announcement effects

Another issue, as mentioned before in Section 4.2, is that of an announcement effect. Although the decision to introduce the Greyhounds was announced in 1988, the analysis presented in this paper takes 1989 to be the treatment year. We formally tested for the possibility of an announcement effect in the difference-in-difference regression framework by adding a lead of the treatment variable to the specifications reported in Tables A1, A4 and A5. The results indicate that while there may be an announcement effect for pcNSDP, this is not the case for the industrial and manufacturing sectors (Table A9 in the online appendix). This confirms the synthetic control methodology results seen graphically in Fig. 2(b) and Fig. 5. A possible explanation for this is that an expansion of the industrial sector involves fixed investments which tend to be less responsive to announcements.

8. Conclusion

Using the synthetic control methodology we show that (i) after 1989, AP's output systematically deviates from a weighted average of the states that it resembles most and (ii) that this deviation cannot be explained by any obvious political or economic factors. As 1989 is precisely the year when AP introduced the Greyhounds, the higher growth post-1989 could be capturing the resulting benefits of improved security. Importantly, this is in line with anecdotal literature that has identified the introduction of Greyhounds as having caused a fundamental shift in the Naxalite conflict.

At the same time it should be stressed that the synthetic control methodology is a case-study approach and that our findings do not imply that other Naxalite affected states raising security forces similar to the Greyhounds would experience effects of similar magnitude. Neither does it imply that a security response is more effective in terms of raising pcNSDP compared to non-security based responses. However, the results presented here are interesting as they show that output and investments respond to counterinsurgency policies.

The field of the microeconomic effects of counterinsurgency policies remains largely unexplored and the dynamics between insurgency, counterinsurgency and economic outcomes are only starting to be understood. As more data become available, future work could measure the effects of Naxalite insurgency and the state's counterinsurgency response at a more disaggregated level.

Acknowledgments

We thank John Strauss, Jeffrey Nugent, Geert Ridder, Rohini Somanathan, Eli Berman, Juan Carrillo, Olga Shemyakina, Raja Kali, Jared Rubin, Subha Mani, Utteeyo Dasgupta, Anant Nyshadham, Channing Arndt, Finn Tarp, Arya Gaduh, Smriti Sharma, Joseph Gomes, two anonymous referees and conference/seminar participants at University of Southern California, Fordham, HECER, Delhi School of Economics, Indian Statistical Institute (New Delhi), ASREC 2013, ISNIE 2012, 8th Annual HiCN Workshop, PACDEV 2011, MWIEDC 2011 and the Institute of Peace and Conflict Studies for helpful comments and suggestions. Singhal gratefully acknowledges financial support from the University of Southern California and UNU-WIDER. Results in this paper supersede those in an earlier working paper entitled “The Economic Costs of Naxalite Violence and the Economic Benefits of a Unique Robust Security Response” (Nilakantan and Singhal, 2011). We take sole responsibility for remaining errors.

[30] Note that spillovers affect the synthetic control estimates only if they affect states that are assigned positive weights in the construction of the synthetic control.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi:10.1016/j.ejpoleco.2016.08.012.

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