UNU-MERIT Working Paper Series

#2014-045

Insurgents in motion: Counterinsurgency and insurgency relocation in Iraq

Pui-Hang Wong

Maastricht Economic and social Research institute on Innovation and Technology (UNU-MERIT)
email: info@merit.unu.edu | website: http://www.merit.unu.edu

Maastricht Graduate School of Governance (MGSoG)
email: info-governance@maastrichtuniversity.nl | website: http://mgsog.merit.unu.edu

Keizer Karelplein 19, 6211 TC Maastricht, The Netherlands
Tel: (31) (43) 388 4400, Fax: (31) (43) 388 4499

UNU-MERIT Working Papers

ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology, UNU-MERIT

Maastricht Graduate School of Governance MGSoG

UNU-MERIT Working Papers intend to disseminate preliminary results of research carried out at UNU-MERIT and MGSoG to stimulate discussion on the issues raised.

Insurgents in Motion: Counterinsurgency and Insurgency Relocation in Iraq

Pui-Hang Wong*

Abstract

Recent studies in general are positive regarding the effectiveness of US counterinsurgency programs in Iraq. The right mix of coercion, ethnic strategy, and public goods provision, it is argued, makes Iraqis less likely to rebel against the US army and the Iraqi government, thus reducing insurgent violence. In fact, the number of insurgent attacks dramatically declined shortly after the change in the counterinsurgency strategy in 2007. How robust is the positive finding? A common assumption behind previous analyses is that insurgent attacks have a strong local root and is unlikely to be reproduced in other areas. Violation of this spatial independence assumption, however, can potentially bias towards the positive result. Based on the novel spatial dynamic panel data (SDPD) model, my analysis shows that spatial dependence should be addressed and cannot be assumed away. Results based on the new model also reveal that, conditional upon other strategies, the effects of a counterinsurgency strategy vary considerably both in magnitude and direction, suggesting that some policy mixes could be counterproductive. Policy makers seeking to adopt similar strategies in Afghanistan should take the relocation into account in their policy evaluations.

Keywords: Counterinsurgency, Sons of Iraq, CERP, Troop Surge, insurgency, Iraq, spillover, spatial dependence, spatial dynamic panel data model, policy evaluation

JEL Classifications: D74, F51, F52, H43, H56, O53.

*Maastricht Graduate School of Governance, Maastricht University and UNU-MERIT. Email address: pui-hang.wong@maastrichtuniversity.nl. The paper was first presented at the International Studies Association's 55th Annual Convention, 26-29 March 2014, Toronto, Canada. I would like to thank Lutz Krebs, Nori Katagiri, and participants at ISA for helpful comments on an earlier version of the analysis.

1 Introduction

Violence in Iraq did not stop after the end of the interstate conflict between the US and Iraq in 2003. Local insurgencies emerged against Coalition and Iraqi forces Hundreds of attacks against the Coalition were recorded every week between 2004 and 2010. Worse still, there was a sustained number of attacks in the first four years after the victory. To reverse the trend, in January 2007, the Bush administration announced the deployment of an additional 20,000 soldiers to the existing 150,000 US troops in Iraq, mainly in Baghdad. The number of attacks however did not subside until it reached a peak of about 1,800 attacks per week in mid-2007. The figure then plummeted in the following months.[1]

Several arguments have been advanced to explain the dramatic turn in the level of violence. One candidate policy factor is the troop surge; the increase in troop density initiated in early 2007 effectively combated the insurgents and deterred future violence. Another prominent view stresses the alliance between the US military and the local tribes (e.g. Long 2008). Under the protection of the US military, the local tribes were able to restore the traditional political order. Some added that the change in military doctrines is responsible for the change. Intelligence from and connections with the local population created a synergy effect with the surge that made the counterinsurgency effort more effective. The alliance can be seen as an exchange between protection and intelligence, therefore two strategies are jointly responsible for the drop (Biddle, Friedman, and Shapiro, 2012). Berman, Shapiro, and Felter (2011) propose that the improved provision of public goods wins the hearts and minds of the people in local communities and induces them to cooperate with the security forces. Emphasizing also hearts and minds, Lynch (2011) however argues that financial incentives would only be accepted hence take effect when the stigma against working with Americans would be reduced by both strategic communications and continuous long-term engagement. The effect of the surge is realized by transforming the relationships with Iraqis through 'endless cups of tea', so the policy effect is not all about coercion. Based on 171 deployment campaigns since World War I, Friedman (2011) also finds that force size has no statistically significant effect on the success of a counterinsurgency strategy. Recent critiques state that domestic political factors could be far more important than the change in the counterinsurgency doctrines and policies (e.g.

[1] A similar pattern is observed when one measures violence differently by looking at civilian or military fatalities.

Hagan, Kaiser, and Hanson 2013; Lindsay and Long 2013). All in all, though there is disagreement on the mechanisms and the (relative) contribution of individual policy remains controversial, the tenability of the synergy thesis is largely deemed positive based on mainly qualitative research. Large-N comparisons across space and time are scant and limited, and the exceptions often focus on one or two policy measures, without explicitly modeling the interaction effect underlying their arguments.

Previous evaluations are not incontestable at a theoretical level. A core assumption behind previous analyses is that insurgencies are heavily restricted by local immobile human geographical factors, and, to some extent, insensitive to counterinsurgency policies, such that insurgency is geographically confined and attacks will not spill over to other geographical units. The spatial independence assumption is proved to be disputable. In the terrorism literature, it has been constantly found that insurgents are reactive to policies and adjust their targets and attack modes swiftly. Admittedly, on the execution level, insurgency does hinge on local factors (e.g. geographical knowledge and advantage), but the local barrier is far from insurmountable and could be overcome by hiring the locals. So violence could be easily reproduced in other areas in the presence of some shared factors such as nationalist sentiment. More importantly, if this kind of spatial interaction prevails, analysis that fails to incorporate the factor would plausibly arrive to a different conclusion and risk providing misleading policy recommendations.

The major contribution of this paper is to quantitatively assess the effects of three major counterinsurgency policies after taking the spatial dependence consideration into account. Given my use of the Iraqi data, the evaluation, hence the policy conclusion, is likely to be context-specific. Nevertheless, in the theory section I will provide a more general framework to conceptualize the issue by listing some relevant factors. In this way the evaluation remains relevant at both theoretical and practical levels.

In the rest of the paper, I will first introduce the target selection framework and list several factors related to insurgent mobility question. I will then explain the significance and relevancy of the argument and point out the empirical consequences of ignoring such mobility issue. An econometric model encompassing spatial dependence will be introduced in the next section, followed by the discussion of the empirical results and conclusion.

2 Insurgent Mobility and Reproducibility of Violence

As established in terrorism literature, it has been repeatedly found that terrorists are calculative and selective when choosing their targets (Crenshaw, 1998; Drake, 1998; Faria, 2006; McCartan, Massell, Rey, and Rusnak, 2008). Insurgents are responsive to the costs of attacks and tend to choose less well-guarded targets and locations. The same holds for the choice of strategies and attack modes (Enders and Sandler, 1993; Jenkins, 1986). For instance, the time series analysis by Enders and Sandler (1993) indicates that counter-terrorism measures designed to reduce one type of attack (e.g. the installation of metal detectors in airports) increases other types of attack such as kidnappings and assassinations. This raises the concern as to whether counterinsurgency creates only a balloon-squeezing effect. Limiting the validity of an analysis, this concern is sometimes acknowledged (Biddle et al., 2012, 22) and recognized (e.g. Hughes 2010, 167; Malkasian 2006, 383), but empirically left unhandled.

Instead of viewing a country as a disconnected set of districts, insurgents are likely to consider the country as a whole and see neighboring districts as spatial substitutes of the heavily deployed districts. Insurgents could move to other less well-guarded locations and achieve similar outcomes by incurring some costs. The perspective constitutes a legitimate challenge to evaluations which simply assume away this possibility by focusing only on local indicators. This is certainly a mismatch between analysis and experience on the ground. In fact, sticking to the local indicators may lead to operations that may spread violence to other locations and create multiple fronts. All in all, the policy conclusion could plausibly be changed if the objectives of an operation have several dimensions that include, for instance, the size of the affected area and the ease of control.

The framework suggests that the validity of the finding in previous studies is dependent to the degree of substitutability between different locations from the perspective of the insurgents. Analyzing the question using an actor-centered approach, this question could be understood as enumerating criteria of target selection or the determinants of mobility. How important are the local human geography factors to the insurgents? How swiftly are the insurgents to adjust their plans and to seed violence in other places? As it is more common that researchers have only regional characteristics in their data sets, if one cannot hope to get a genuine answer from insurgents, an analytic framework based on local factors is beneficial. While the following enumeration does not mean to be exhaustive, it proves to be helpful for an early analysis of its ilk.

In short, reproducibility of violence depends on the significance of various geographical and human-related factors to the insurgents. Factors include but are not limited to geography, socio-economic characteristics, customs, and human relations between the insurgents and the inhabited groups. These factors carry different weights in insurgents' calculus. As the weights of factors vary from case to case, the net effect is usually ambiguous and is a ultimate empirical question. Generally speaking, if the local factors are deemed to play a more crucial role, one would expect that violence is more difficult to be bred. On the other hand, if the location-specific factors are less critical to the rebel group, substitution is more likely to be seen. Note that a single factor could work through multiple mechanisms and factors could be inter-related.

A number of factors are particularly relevant in the Iraqi context. The first is economic well-being. Destitution, income inequality and poor living conditions may create grievance among local communities (Cederman, Weidmann, and Gleditsch, 2011). Economic deprivation could reduce the opportunity costs of recruiting a rebel (Fearon and Laitin 2003; Humphreys and Weinstein 2008). The change of living conditions may motivate Iraqis to take revenge by attacking the Coalition forces who are thought to be occupying their land. Hughes (2010, 159) indicates that many insurgencies against the Coalition were initiated by the humiliated and impoverished ex-officers of the demobilized Iraqi army. The perceived failure to reconstruct the country could inspire resentment among Shias and Sunnis alike. If this perception is widespread in Iraq, insurgencies would have a wider base to breed violence. Attacks, in consequence, would be less likely to be geographically confined. On the other hand, if poverty is confined to a certain area, or income inequality is the factor to be blamed, insurgents may find it more difficult to reproduce violence in regions where people are more satisfied with their lives.

The second factor is natural resources. Oil, gas, and pipelines are unequally distributed in Iraq. If the resource revenue is essential to the survival and activities of the insurgents, insurgents are more likely to stay close to and safe-guard the resources (Buhaug and Rod 2006; Ross 2004). Insurgents are also less likely to be incentivized to move beyond their control zones to initiate attacks in regions where they have no immediate interests. In cases where insurgents do not control the territory, if attacks are inevitable, insurgents are more likely to find resource-rich regions particularly attractive. Hughes (2010, 165) documents that Sunni insurgents targeted the power grid and oil industry, with an intention to sabotage reconstruction and to intensify discontent among Iraqis, a logic related to the economic factor discussed before.

The third candidate factor is demographic distribution. Whether an ethnic group has motivation to attack is found dependent to the power shift and configuration of the group in the polity (Cederman, Gleditsch, and Buhaug 2013; Cederman, Wimmer, and Min 2010). Sunnis who were attached to the Ba'ath regime lost their privileged political position after the war (Hughes, 2010). This factor is indeed found strongly associated with the attacks, at least in the early years following the invasion (Berman et al. 2011). Public opinion surveys carried out in 2006 and 2007 reveal that over 90% of Sunnis had a negative opinion towards the presence of the US, felt that the US negatively influenced the situation in Iraq and emotionally supported the attacks (Lynch, 2011, 49-50). In this case, Sunnis may find it difficult to export violence to, for example, Kurdish-dominated areas. On the other hand, the nationalist resentment could be shared by many Iraqi and nationalists outside Iraq. Power struggles within and among different religious groups also led violent outbidding a viable strategy to gain public support (Hughes, 2010, 159-161). In this way, nationalism and political competition may lead insurgencies not to be bounded locally.

Information problem is universal to all kinds of attacks. The contents of information are usually location-specific. Though insurgents are highly mobile and can, for example, install improvised explosive devices (IEDs) in other localities, the lack of local knowledge could bar insurgents to effectively organize an attack without receiving some help from the locals. Information related to routes for logistics and retreats, and locations that maximize enemy casualties are examples of parameters of concern to insurgents. In fact, an argument for the effectiveness of the new counterinsurgency doctrine is that it engages the locals to provide intelligence, which helps security forces to identify and expel outsiders (Biddle et al. 2012; Lyall 2008; Lynch 2011). In short, if the information problem is a severe constraint, the likelihood and success rate of reproducing attacks elsewhere will be reduced.

Tribal politics and networks among local elites and political leaders could inhibit violence. Long (2008) and Hughes (2010) consider that Al-Qaeda's violent coercion against Sunnis in Anbar created an opportunity for the US military to ally with the Anbar Salvation Council. Anger and insecurity catalyzed local tribes and the military to cooperate, which laid down a foundation for the coming political change that contributed to the success of the tribal strategy. Also related are ethnic and tribal relations and social norms. If the social groups of concern are in enmity or have a rigid conception of territory, insurgents would become more reluctant to cross the regions or to buy-off people of other groups, although the social labels sometimes could be fluid and multi-layered. If that is the case, diplomacy or political exchanges among tribes will help insurgents to overcome information constraint. Inter-tribal cooperation and facilitation could vary at different levels. Cooperation could take many forms, such as contracting out attacks, offering assistance in terms of resources and intelligence, or simply turning a blind eye to the attacks and refusing to share intelligence with the military. A neutral local group may not want to be involved or become a scapegoat, and consequently refuse to cooperate or choose to report to local security forces. On the other hand, groups in constant conflict, for example, such as Sunni and Shia, would find cooperation or alliance more difficult.

Finally, some locations possess higher strategic or symbolic values than the others. Controlling them is deemed desirable (Goddard, 2006). Examples are Baghdad and Najaf. In that case, insurgents will be more willing to tolerate loss or to incur costs to gain control of the region, instead of replacing it with substitutes of lower value to them.

3 Empirical Consequences of Ignoring the Issue of Insurgent Mobility

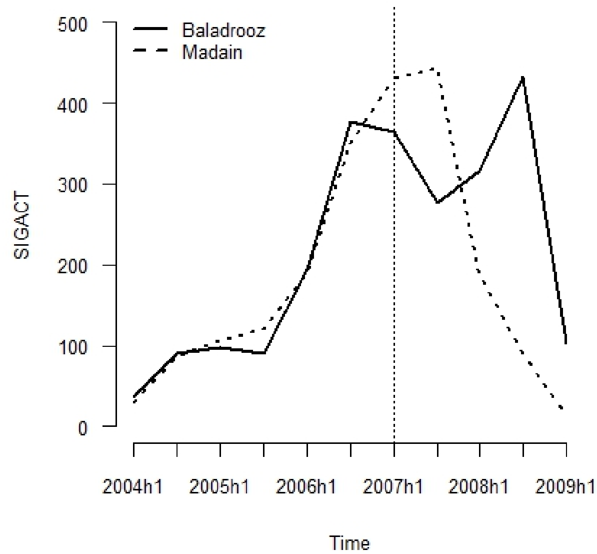
Whether target substitution is real or not,, why should analysts care about it? When relocation is common, reduction of violence in one district means a higher level of violence in neighboring districts. Focusing on the temporal pattern of violence in one region and ignoring the possibility of spatial spillovers would paint an overly optimistic picture regarding the effectiveness of the counterinsurgency strategy under consideration. Recall that in a large-N setting the finding of a strategy being effective in reducing violence is based on the assumption that other districts which enter the analysis constitute a qualified control group. If displacement of violence is widespread, this cross-unit interdependence violates the stable unit treatment value assumption (SUTVA) commonly made in analysis. The violation renders results even obtained from an experimental setting biased (Franzese and Hays, 2008, 760). Subject to interdependence, the analysis risks incurring omitted variable bias and exaggerating the effect of the counterinsurgency strategy under evaluation. The bias cannot be corrected by simply clustering the standard errors (Franzese and Hays 2007; Franzese and Hays 2008, 754-757).

In our Iraqi case, the logic suggests that seeing that the violence level dropped in Baghdad in comparison with that of in Baladrooz, a district bordering Mada'in in Baghdad, is not enough, as the trend in Baladrooz is 'contaminated' if relocation occurs. In fact, the rise in the level of violence in the control regions like Baladrooz will lead to an overestimation to the effectiveness of the counterinsurgency programs under comparison. This is true even if the violence was unabated in the presence of a counterinsurgency program because the level of violence was in fact increased in the 'control' district. Data suggest that the relocation which we worry about was likely to happen. Figure 1 plots the (weekly) number of attacks in Baladrooz and Mada'in between 2004 and the first half of 2009, a period covering the surge and other counterinsurgency measures active in 2007.[2] Two districts share a similar trend in the beginning, but the trend of violence diverges shortly after 2007. More importantly, the number of attacks in Baladrooz increased shortly after a drop in Mada'in starting from late 2007; a pattern consistent with the displacement hypothesis. Moreover, a naive extrapolation of the trend in Baladrooz suggests that the violence might be around 250 attacks per week in the second half of 2008, instead of over 400 attacks that we actually observed. This implies that if violence spilled over to Baladrooz, the effectiveness of the counterinsurgency program could be exaggerated if it is not an artifact of the contamination due to the spillover. The widening gap between two districts due to relocation would lead analysts to wrongly conclude that the program was highly effective. All in all, the illustration is not to mean that the rise must be caused by joint counterinsurgency effort in 2007. Yet, the example legitimizes the theoretical and empirical concerns that have been discussed. Both issues should be properly addressed.[3]

[2]Recorded in the Multi-National Forces Iraq (MNF-I) SIGACT III database. 'Significant activities', or SIGACT, is the count number of attacks considered to be targeted against the Coalition forces.

[3]A recent study by Romano et al. (2013) assesses the impacts using time-series analysis by pooling all districts together, in order to avoid the interdependence problem mentioned here. But the design does not allow us to test and gauge the spillover effect that this paper aims to address.

Figure 1: Shift of Insurgency from Madain to Baladrooz



In summary, the interplay among a myriad of factors discussed in the previous section makes it hard to predict to what extent displacement of violence was present and may bias a result; this is ultimately an empirical question. While data availability disallows me to disentangle the effect of each individual factor discussed before, three questions of particular interest are answerable:

1. Is spatial interdependence in the Iraqi case an issue severe enough to revise previous research findings?

2. What are the marginal contributions of various counterinsurgency policies to the reduction of violence?

3. Is there a synergy effect between programs?

The following section will introduce the econometric model used to analyze the issues.

4 Data and Method

Data for the analysis are based on Berman et al. (2011). The dependent variable is the number of attacks against the Coalition forces. The measure is by no means perfect (see Berman et al. (2011, 790). But it is one of the most detailed and consistent measures available and widely used in other quantitative studies such as Berman et al. (2011), Biddle et al. (2012) and Romano et al. (2013). I do not distinguish various types of attacks to allow substitution among attack modes. There are three independent variables of particular interest. The first is the change in the number of brigades in 18 governorates between the second half of 2006 and the first half of 2008. The variable records not only the surge of the US military but also of the Iraqi Army, including (military) national police and border enforcement, a surge far more substantial than that of the US in terms of scale. As there is no high-resolution data prior to the period (i.e. details on both time and locations) available, the treatment implicitly assumes that there is no change in deployment before the second half of 2006, which is certainly not true. Whether this may lead to an underestimation of the contribution of the surge is unknown. On one hand, the withdrawal of the Multi-National Force might lead to the an escalation of violence in Iraq;[4] on the other hand, the expansion of the Iraqi Army could enhance the security of the region. Overall, if one tends to believe that the Multi-National Forces are the unmissable security providers to the country (Hughes, 2010, 158; 167), the failure to account for their role before the surge would lead to an underestimation of their contribution of the surge. In this way, the estimated effect is likely to be a lower-bound effect of the program. To reduce the impact of the assumption, I rely on the time dummy variables to absorb this country-wide policy change. The treatment is certainly far from perfect. But the addition of this surge variable, which is absent in previous studies, should substantially improve the validity of the evaluation.

The other two independent variables are expenditures in two types of projects: the Commander's Emergency Response Program (CERP) and the Sons of Iraq (SOI). Data for the CERP projects records non-SOI related expenditures on reconstruction in Iraq. Projects cover areas like education, health, and transportation. Given the public goods nature, the variable is adjusted for the sizes of population and of the district. The cross-section unit is district and the time unit is half-year. As most projects last for several months, the six-month window allows the projects to complete and to bring benefits perceivable to the local communities (Berman et al., 2011). Other control variables include population, an index of satisfaction with local public goods provision, income, and pipeline volume (weighted by price of oil and gas and adjusted for inflation), I also constructed

[4] The major cutting back of the British military was in 2003 and 2004 (Hughes, 2010, 158). The period was not covered in my sample after lagging the variables to fit in the model.

three dummy variables that indicate whether a district is dominated by Sunni, Shia, or mixed with Sunni, Shia, and/or Kurdish; the reference group is Kurdish. To avoid reverse causality, the policy and resources variables are lagged one period.

The basic model, which does not contain spatial weight term, is first estimated with the ordinary least square (OLS). Estimation then is extended to the fixed-effect model with time dummies, that is, the two-way error-component model in Baltagi (2005). The fixed-effect model is able to control for selection effects due to any time-invariant, district-specific characteristics. The model is also able to control for most of the immobile human-geographical factors, which are likely to be time-invariant, discussed in the earlier sections.

I proceeded by estimating the following spatial model using maximum likelihood estimation with a modified likelihood function (Ord, 1975):

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \theta \sum_{j=1}^{N} w_{ij} x_{jt} + \gamma x_{it} + \beta z_{it} + \mu_i + \pi_t + \varepsilon_{it} \tag{1}$$

In the above model, y is the dependent variable, w the spatial weight, x the explanatory variable hypothesized to exert both spatial and non-spatial effect to y, z other explanatory variable, μ the district-specific effect, and π the time-specific effect.[5] The significance of the spatial effect could be evaluated based on the Wald test (Anselin, Le Gallo, and Jayet, 2008). The spatial Durbin model, rather than the more common spatial lag or spatial error models, is estimated as it is more general (see footnote 5) and generates results that better match our research interests.[6] Spatial substitution exists when $\theta > 0$. Literally, it says the violence level in district i would increase as the intensity of counterinsurgency policy x in neighboring district js increases. If $\theta < 0$, one may interpret the counterinsurgency has a preemption effect; counterinsurgency in that case not only helps reduce violence in the operated regions but their neighborhoods as well.

The model above could be restrictive in the sense that only time-invariant omitted variable is controlled for. To better capture the omitted time-varying effect, the dynamic panel model that includes a lagged dependent variable, which summarizes the recent history of violence in the unit,

[5] To avoid burden the equation, the case where there is only one x and z variable is shown. This spatial Durbin model could be reduced to the more common spatial lags or spatial error models if certain restrictions on the parameters are imposed (LeSage and Pace, 2009). Since the research interest is the significance of the spatially lagged explanatory variables, I estimate the full model without imposing any parameter restrictions in the investigation.

[6] See Elhorst (2012).

is also estimated (Angrist and Pischke, 2009).

$$y_{it} = \tau y_{i,t-1} + \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \theta \sum_{j=1}^{N} w_{ij} x_{jt} + \gamma x_{it} + \beta z_{it} + \mu_i + \pi_t + \varepsilon_{it} \tag{2}$$

To estimate the spatial dynamic panel model, the quasi-maximum likelihood estimator by Yu, de Long, and Lee (2008) designed for spatial panel model is employed. The estimator not only accounts for the endogeneity related to the spatial term and the lagged dependent variable, it also performs well by requiring only either N or T to be large (Lee and Yu, 2010a). A follow-up Monte Carlo study by Elhorst (2010) found that the estimator outperforms the GMM estimator in terms of biasness when T is small, a situation we have in the present case. One may argue for an alternative model such as Poisson or negative binomial for count data, but the property of those estimators is unproven in a spatial dynamic setting. For this reason, I treat the dependent variable as a continuous one. In fact, upon data transformation (i.e. de-meaning), the dependent variable that enters the maximum likelihood is continuous and contains negative values.

Care has to be taken when evaluating the marginal effect of an explanatory variable as the dependent variable now appears on both sides of equations (1) and (2) in the presence of the spatial lag. A statistically significant coefficient does not necessarily mean that the explanatory variable has a statistically significant effect (Franzese and Hays 2007, 2008). To see this, rewrite equation (1) in matrix form as

$$Y = WY\delta + WX\theta + X\gamma + Z\beta + P_\mu \mu + P_\pi \pi + \varepsilon$$

, where $P_\mu = \iota_T \otimes I_N$ and $P_\pi = \iota_N \otimes I_T$ are the district-specific and time-specific effects. After collecting terms and taking the partial derivative, the marginal effect of X_k is,

$$\frac{\partial Y}{\partial X_k} = \begin{bmatrix} \frac{\partial Y}{\partial x_{1k}} & \cdot & \frac{\partial Y}{\partial x_{Nk}} \end{bmatrix} = \begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdot & \frac{\partial y_1}{\partial x_{Nk}} \\ \cdot & \cdot & \cdot \\ \frac{\partial y_N}{\partial x_{1k}} & \cdot & \frac{\partial y_N}{\partial x_{Nk}} \end{bmatrix} = (I_N - \delta W)^{-1} \begin{bmatrix} \gamma_k & w_{12}\theta_k & \cdot & w_{1N}\theta_k \\ w_{21}\theta_k & \gamma_k & \cdot & w_{2N}\theta_k \\ \cdot & \cdot & \cdot & \cdot \\ w_{N1}\theta_k & w_{N2}\theta_k & \cdot & \gamma_k \end{bmatrix} \tag{3}$$

The resulting matrix is a square matrix with dimensions N by N, with N equal to the number of districts. The matrix summarizes the marginal effects of the explanatory variable X_k to Y. Each element in the matrix represents the marginal effect related to the explanatory variable x_k in district j (row) on the dependent variable in district i (column). For example, consider the square matrix corresponding to the variable CERP spending. The element at row 10 and column 5 tells us the marginal effect of CERP spending in district 10 on the violence level at district 5, after taking into account the possible feedback, which is picked up by the term $(I_N - \delta W)^{-1}$.[7] By feedback, it means the effect of violence in i to j (first-round), and from j back to i, and from i to j (second-round), and so on. The diagonal elements in the matrix is the direct effect of the explanatory variable (i.e. policy at district i on violence in the same district); all the off-diagonal elements represent the indirect effect (i.e. spillover effects). As each element in the matrix is district-specific, so it would be inconvenient to report the district-by-district effect.[8] Consequently, the average marginal effects will be reported. To do so, one can take the average of the corresponding elements: that is, the average of all diagonal elements for the average direct marginal effect, and the average of either the row sums or the column sums of the off-diagonal elements for the average indirect marginal effect (LeSage and Pace, 2009).

The last equality in equation (3) clearly shows that the direct marginal effect of X_k on Y is determined by two parameters: δ and γ_k, which interact non-linearly. Given the interaction, care also has to be taken to make statistical inferences concerning the marginal effects, as the standard error of the estimated coefficient γ_k is different from the standard error of the marginal effect, which depends on both δ and γ_k. To correctly evaluate the statistical significance of the marginal effect, I used the simulation method to construct the empirical distributions of the simulated marginal effects based on the estimates and the information matrix (Greene 2011). The simulation exercise is functionally akin to the familiar t-test in usual regression analysis. The complication here is necessary because, to recap, the marginal effects of the explanatory variables are not identical to their corresponding coefficients in model with a spatially lagged dependent variable on the right hand side of the equation.

[7] See Ward and Gleditsch (2008) on the multiplier effect.

[8] For example, with 104 districts in our case, there are $104 \times 104 = 10,816$ marginal effects for each variable X_k per period. From equation 3, it should be clear that the variation is driven by the spatial weights.

5 Results

The estimation results are reported in Table 1. Results based on OLS estimation, which is contained in column 1, are somewhat consistent with our expectations: Areas dominated by Sunni or mixed Sunni with Shia recorded a higher number of attacks; some counterinsurgency measures are effective in reducing the level of violence, resources and income level, however, are not statistically significant. The results in general suggest that the attacks to Coalition Forces are not economic or greed-driven but mainly political.

Findings based on the OLS estimation, however, are likely to be affected by the selection effect. For this reason, I also estimated the fixed-effect model which better controls for the selection effect due to time-invariant factors. Added to the benchmark is the static spatial panel with both district-effect and time-effect. Statistical significance of the coefficient corresponding to the spatial term suggests that spatial interaction has a statistically significant role to play in the process. In other words, failing to consider the spatial dimension has a potential to bias the estimation of the policy effects.

One major limitation of the static models is that it fails to account for the short-term dynamics of violence, which interests policy makers the most, as counterinsurgency is likely to be responsive to recent change in the level of violence hence not time-invariant. Adding a lagged dependent variable, which summarizes the immediate unit history, to the right hand side of the model allows me to better account for the short-run adjustment dynamics of violence in response to counterinsurgency policy. The estimation results of the more general model are reported in the last column. The coefficients related to the spatially and temporarily lagged dependent variables are sum to $0.892 < 1$ (i.e. $1.297 - 0.405 = 0.892$). In other words, the series is stable and non-explosive (Lee and Yu, 2010b).

As discussed in the previous section, with the multiplier effect, coefficients interact non-linearly. The statistical significance of the lower-order coefficients also has a specific interpretation; that is, the effect is conditional on the other constitutive term equal to zero (Brambor et al., 2006; Braumoeller, 2004). Consequently, one cannot easily evaluate the marginal effect and its statistical significance by simply reading from Table 1. For illustration, consider the marginal effect of SOI. Based on equation (3), the marginal effect of SOI on SIGACT at time t is:

Table 1: Estimation Results

	Dependent variable: *SIGACT*			
	(1)	(2)	(3)	(4)
	OLS	FE	Spatial	Dyn. Spatial
SIGACT_{t-1}				1.297***
				(0.045)
W.SIGACT			-0.442***	-0.405***
			(0.081)	(0.109)
SOI_{t-1}	-0.827	-1.042	-1.125**	-0.423
	(0.672)	(0.862)	(0.549)	(0.534)
CERP_{t-1}	12.097	2.529	1.875	-1.242
	(7.823)	(5.191)	(2.555)	(2.531)
Surge_{t-1}	0.140	0.076	0.112	0.843***
	(0.358)	(0.155)	(0.264)	(0.273)
$(\text{SOI} \times \text{CERP})_{t-1}$	0.028	-0.426**	-0.418***	-0.114
	(0.196)	(0.214)	(0.123)	(0.120)
$(\text{SOI} \times \text{Surge})_{t-1}$	-0.011	-0.074**	-0.079***	-0.047***
	(0.020)	(0.031)	(0.017)	(0.017)
$(\text{CERP} \times \text{Surge})_{t-1}$	0.335**	0.095	0.096	-0.551***
	(0.165)	(0.071)	(0.068)	(0.072)
$(\text{SOI} \times \text{CERP} \times \text{Surge})_{t-1}$	-0.004	0.009*	0.010***	0.011***
	(0.004)	(0.005)	(0.003)	(0.003)
Resources_{t-1}	-0.025	-0.084	-0.066	-0.176
	(0.064)	(0.057)	(0.097)	(0.115)
ln(population)	131.744**	39.531	26.024	-52.608
	(61.085)	(36.218)	(58.985)	(46.578)
W.SOI_{t-1}			-4.772	-6.432
			(5.298)	(4.239)
W.CERP_{t-1}			-27.049	69.507***
			(16.559)	(25.369)
W.Surge_{t-1}			3.794	30.844***
			(2.611)	(3.373)
$\text{W.}(\text{SOI} \times \text{CERP})_{t-1}$			0.910	4.751***
			(1.223)	(0.911)
$\text{W.}(\text{SOI} \times \text{Surge})_{t-1}$			-0.285*	-0.004
			(0.164)	(0.136)
$\text{W.}(\text{CERP} \times \text{Surge})_{t-1}$			-1.198**	-4.637***
			(0.542)	(0.760)
$\text{W.}(\text{SOI} \times \text{CERP} \times \text{Surge})_{t-1}$			0.067***	-0.018
			(0.024)	(0.023)
W.Resources_{t-1}			0.141	-2.102***
			(0.280)	(0.897)
Sunni	245.295**			
	(94.710)			
Shia	-55.635			
	(35.490)			
Mixed	285.786***			
	(71.205)			
Income	25.742			
	(21.771)			
Public goods	-4.432			
	(13.968)			
Constant	-1522.472**	-368.171		
	(740.235)	(442.030)		
District effect	No	Yes	Yes	Yes
Time effect	No	Yes	Yes	Yes
Observation	900	936	936	832
No. of districts	100	104	104	104
No. of periods	9	9	9	8
Note:	*p<0.1; **p<0.05; ***p<0.01			

$$\frac{\partial SIGACT_t}{\partial SOI_{i,t-1}} = \underbrace{(I_N - \delta W)^{-1}}_{\text{multiplier effect}} \begin{bmatrix} \Gamma_{i,t-1} & w_{12}\Theta_{j,t-1} & \cdot & w_{1N}\Theta_{j,t-1} \\ w_{21}\Theta_{j,t-1} & \Gamma_{i,t-1} & \cdot & w_{2N}\Theta_{j,t-1} \\ \cdot & \cdot & \cdot & \cdot \\ w_{N1}\Theta_{j,t-1} & w_{N2}\Theta_{j,t-1} & \cdot & \Gamma_{i,t-1} \end{bmatrix} \tag{4}$$

where

$$\Gamma_{i,t-1} \equiv \underbrace{\underbrace{\gamma_{\text{s}}}_{\text{own}} + \underbrace{C_{\textit{i,t-1}} \times \gamma_{\text{s,c}}}_{\text{interact with CERP}} + \underbrace{TS_{\textit{i,t-1}} \times \gamma_{\text{s,TS}}}_{\text{interact with the surge}} + \underbrace{C_{\textit{i,t-1}} \times TS_{\textit{i,t-1}} \times \gamma_{\text{s,C,TS}}}_{\text{interact with CERP and the surge}}}_{\text{direct effect}}$$

$$\Theta_{j,t-1} \equiv \underbrace{\underbrace{\theta_{\text{s}}}_{\text{own}} + \underbrace{C_{\textit{j,t-1}} \times \theta_{\text{s,c}}}_{\text{interact with CERP}} + \underbrace{TS_{\textit{j,t-1}} \times \theta_{\text{s,TS}}}_{\text{interact with the surge}} + \underbrace{C_{\textit{j,t-1}} \times TS_{\textit{j,t-1}} \times \theta_{\text{s,C,TS}}}_{\text{interact with CERP and the surge}}}_{\text{indirect effect}}$$

with S denoting SOI, C CERP, TS troop surge, and the associated subscripts correspond to the coefficients of the (interacted) explanatory variables in the full mode. The expressions are much longer in our full model that includes interaction terms.

Three observations should be noted by inspecting the expressions. First, the total marginal effect is equal to the multiplier effect times the direct effect and indirect effect. Each of the direct and indirect effect has four components: one associated with SOI itself, two interaction terms associated, respectively, with CERP and the surge, and one synergy effect associated with both CERP and the surge. Second, there is a time subscript attached to the policy variables which considered to have a synergy effect with SOI. It means that the marginal contribution of a policy in the presence of synergy effect is time-varying. Finally, the marginal effect of a counterinsurgency strategy is asymmetric in the presence of a synergy effect. For instance, consider the synergy effect between SOI and the surge. With synergy, the marginal contribution of *SOI* depends on the prevailing status of the *surge*. In parallel, the marginal contribution of the *surge* depends on the prevailing status of *SOI* as well. Though we are evaluating the same synergy effect between SOI and the surge, the marginal effects are different and depending on which other policy variable is held fixed (and at what value). The asymmetry implies that if there is a synergy effect between SOI and the surge, policy makers should carefully think about which strategies they want to adjust, as the effect of lowering SOI (and holding the surge fixed) and of lowering the surge (and holding SOI fixed) may not have the same sign and size, with an effect depending on the estimates and other variables.

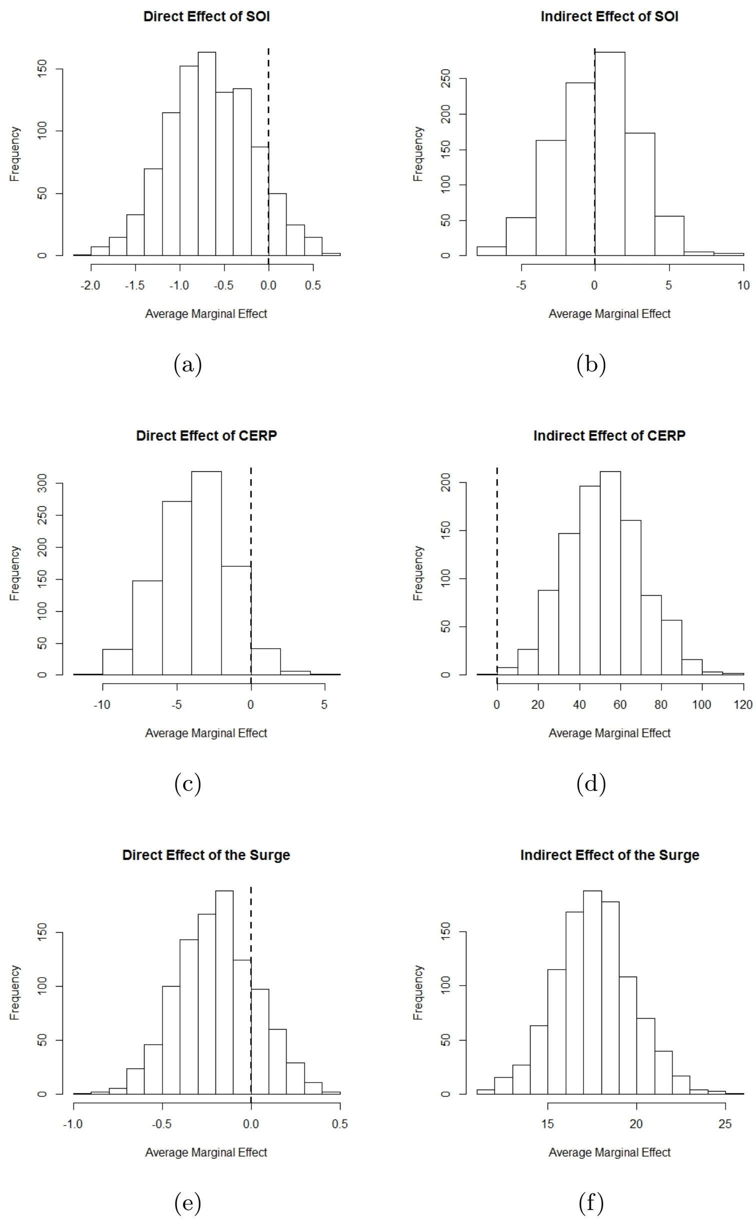


Figure 2: Aggregate Marginal Effects

In the following, I report the net or aggregate effects first, then the decomposition, both based on estimates obtained based on model (4). Figure 2 illustrates the (net) marginal effects of three policy variables. Since the marginal effects are time-varying, here I report the marginal effect based on the period-average of the policy variables, with 95% confidence interval. The tails are trimmed and not shown in the diagrams, so if the distributions covers 0, shown with a dotted vertical line, it signifies that the marginal effect is statistically insignificant at 5% level.

Because one cannot adjust SOI without changing, for example, SOI $\times$ Surge and SOI $\times$ CERP, Figure 2(a) essentially tells us that by slightly reinforcing SOI in a district, the average effect on the implemented district is likely to be violence-reducing, though the aggregate effect is not statistically significant at 5% level. The policy is not effective in reducing the number of attacks in the neighboring districts as well (Figure 2(b)). CERP has a similar effect in an implemented district (Figure 2(c)), but the same policy is very likely to increase the number of attacks in the neighboring districts (still a number of cases fall inside the 95% confidence interval, see Figure 2(d)). Finally, the effect of troop surge is similar to CERP, with a statistically significant spatial spillover effect (Figure 2(f)). Troop surge essentially drives out insurgents to other regions and spreads violence to its neighborhood.

The above findings suggest that the policies in general do not carry out the intended effects. But the aggregate effect may not be very informative. Different synergy effects may have marginal effects opposite in sign, and the heterogeneity renders particular counterinsurgency strategy void in net terms. For this reason, we would also want to see if different combinations of policy work in particular ways. For this reason, we turn to the decomposition. Again, the period-averages and confidence intervals are reported. We consider the direct effect first, that is, the marginal effect on the implemented districts. The results are provided in Figure 3. The results corresponding to SOI are contained in the first column, to CERP the second, and to the surge the third. Figures in the first row inform us the marginal effect of the policy in consideration by holding the other two polices fixed at its period-average values. Overall, if a district has all three policies active, increasing the intensity of whichever policy, the effect is similarly violence-enhancing; all statistically significant at 5% level. The second and the third rows give the marginal effects of a particular policy when one of the other policy held fixed and the third at zero.[9] Highly likely to be violence-reducing is SOI with surge held fixed at period-average and CERP at zero (Figure 3(g)), so does its counterpart (Figure 3(f)). The effects of the combinations between CERP and the surge with no SOI is also promising (Figures 3(h) and 3(i)); both are statistically significant at 5% level. Lastly, figures on the final row

[9] See Braumoeller (2004) for the conditionality interpretation.

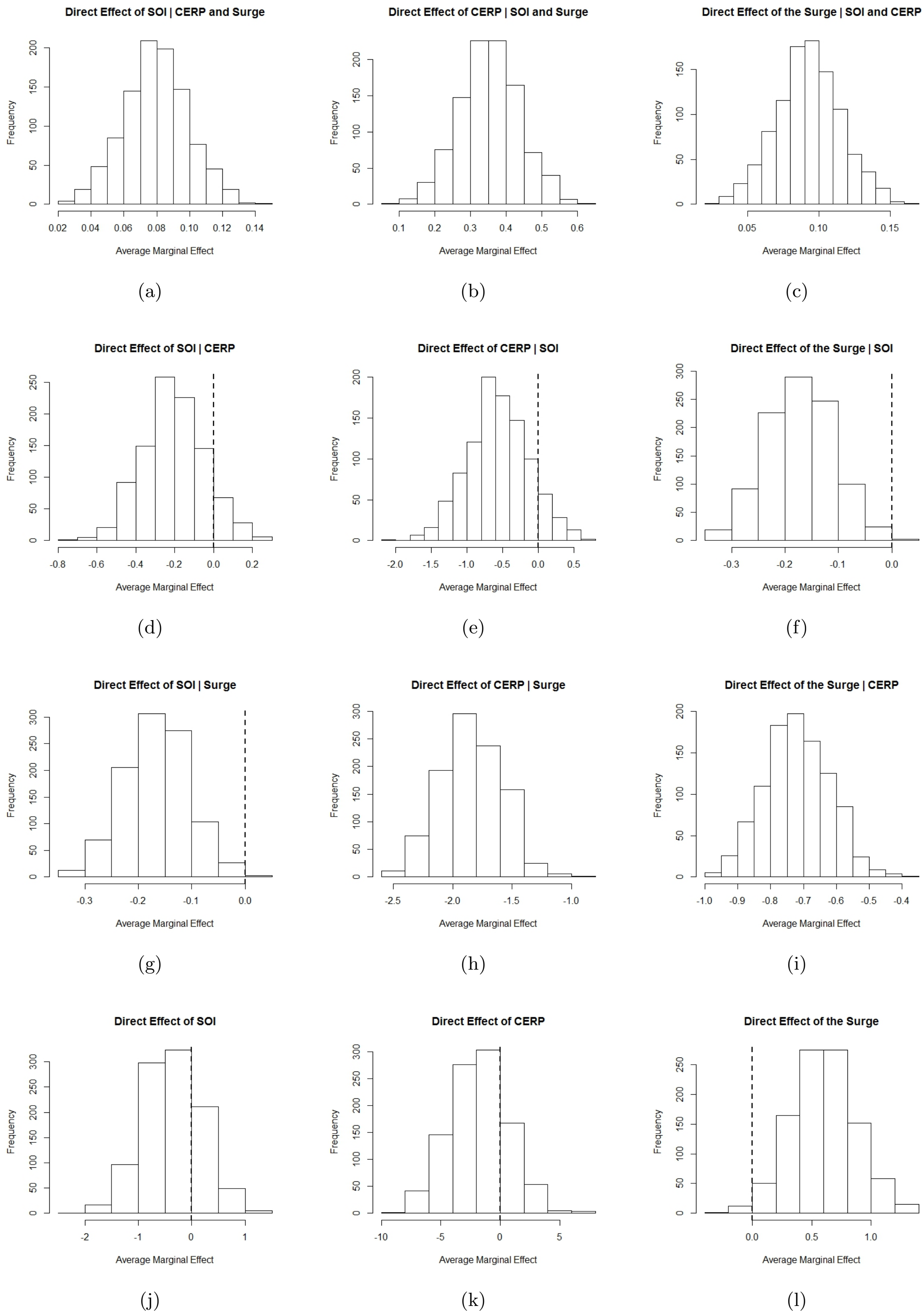


Figure 3: Marginal Effects (Direct)

informs us how a particular policy works when the other two were absent in a district. SOI and CERP are not likely to work in isolation (Figures 3(j) and 3(k)), confirming the synergy thesis by Biddle et al. (2012) and the logic in Berman et al. (2011). Surprisingly, the surge is likely to increase violence even in the implemented district. But given the model specification, this harmful effect can only be said to be present in short run. Though this finding sounds counter-intuitive, Biddle et al. (2012) and Lindsay and Long (2013) invariably point to the spike of violence shortly after the surge. So do Romano et al. (2013): troop surge in the short run causes more confrontations and back-fires; so the positive effect.

Consider the indirect or spillover effects. In general, the implementation of all three policies together is not particularly likely to produce a negative spillover effect (Figures 4(a) to 4(c)). Some duos, however, are dangerous. The SOI-surge pair, with no CERP on the ground, has no apparent spillover effect (Figures 4(f) and 4(g)). While the CERP-surge pair, with no SOI, reduces violence in the neighborhood (Figures 4(h) and 4(i)), the implementations of SOI and CERP without surge could drive insurgents elsewhere (Figures 4(d) and 4(e)). Considering each counterinsurgency policy alone, both CERP and troop surge, without some mixes of other policies, are likely to breed violence elsewhere (Figures 4(k) and 4(l)). The fare of SOI is better, but the negative effect is far from certain (Figure 4(j)).

Table 2: Results Comparison

Row	SOI	CERP	Surge	Direct	Indirect	Synergy	Hearts & Minds
(1)	$\star$	mean	mean	$\Uparrow$	0	Synergy?	Hearts & Minds?
(2)	$\star$	mean	0	0	$\Uparrow$	Not specified	Hearts & Minds?
(3)	$\star$	0	mean	$\downarrow$	0	$\Downarrow$	Not specified
(4)	$\star$	0	0	0	0	0	Not specified
(5)	mean	$\star$	mean	$\Uparrow$	0	Not specified	$\Downarrow$
(6)	mean	$\star$	0	0	$\Uparrow$	Not specified	$\Downarrow$
(7)	0	$\star$	mean	$\Downarrow$	$\Downarrow$	Not specified	$\Downarrow$
(8)	0	$\star$	0	0	$\uparrow$	Not specified	$\Downarrow$
(9)	mean	mean	$\star$	$\Uparrow$	0	Synergy?	Hearts & Minds?
(10)	mean	0	$\star$	$\downarrow$	0	$\Downarrow$	Not specified
(11)	0	mean	$\star$	$\Downarrow$	$\Downarrow$	Not specified	Hearts & Minds?
(12)	0	0	$\star$	$\uparrow$	$\Uparrow$	0	Not specified

Table 2 summarizes and compares my findings (based on Figures 3 and 4) with the existing literature. The star in column one to three denotes the marginal effect being evaluated. 'Mean'

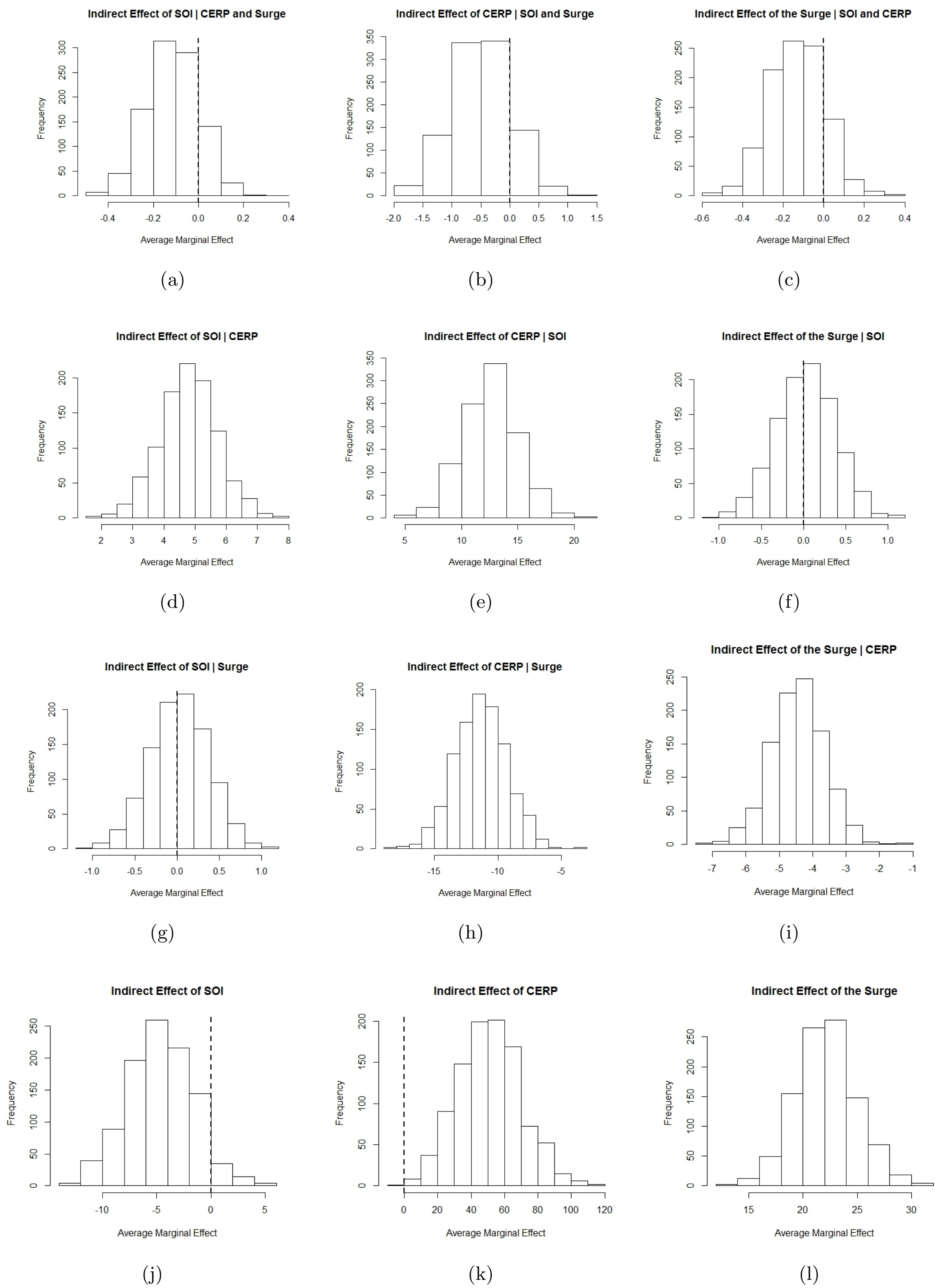


Figure 4: Marginal Effects (Indirect)

and '0' indicate the conditions of the marginal effect. Arrows with a double vertical line signify that the conditional marginal effects are statistically significant at 5% level while the one with a single vertical line states that the effects are significant at 10% level. For example, row one is read as: higher intensity of SOI would increase the average level of violence when both CERP and the surge are conditional at their mean values. And the result is significance at 5% level. Under the same conditions, the average level of violence is not influenced by SOI in the neighboring districts in statistical terms.

Two observations follow from the table. First, it is obvious that the marginal effects of the same policy are very diverse and depending on the status of two other policies (e.g. compare rows 1 to 4). Second, the danger of generalizing the policy effect without specifying the conditions of other policy becomes clear. For example, in evaluating the synergy effect, that is, the interaction between SOI and the surge, while the results contained in rows 1, 3, 9, 10 are quite different, all could be consistent with the synergy thesis. The policy effect, however, is quite different. Worse still, not all of them work in the desired directions.

Overall, spatial spillover in some cases is real and considerable. But some policy-mixes help alleviate the side-effect. Also worth noting is that some policy mixes (e.g. the SOI-CERP pair) have opposite effects in the implemented and neighboring regions. More importantly, while the claims in previous studies are usually unconditional, my study shows that the effects are far from universal. Some combinations work better than others only when certain policy is held fixed or absent. Disregarding the conditionality could lead to undesirable policy outcomes. The effects of different strategies are non-additive. No counterinsurgency strategy (or its mix) is perfect and works unconditionally.

6 Conclusion

Previous sub-national analyses in counterinsurgency in Iraq usually make an implicit assumption that different units are independent. When the assumption is violated, the assessments could be biased towards the positive findings. This issue is more prevailing in sub-national analysis as the barriers to trans-administrative unit activities are often low. This study introduces a target selection approach to the insurgent mobility problem. While the net effect of counterinsurgency strategy is always context-dependent, this study discusses a number of factors relevant to the problem and a novel tool portable to similar kind of analyses. Applying the framework and method to the Iraqi data, I found evidence showing that spatial interdependence should be taken seriously in the assessment exercise. The effects of a counterinsurgency strategy could vary considerably across space when mixed with other strategies. As the effect is usually conditional on the use of other strategies, no single strategy is a panacea. This caveat is especially important as similar strategies have been adopted in Afghanistan. The findings here are not to suggest to abandon the strategy of the surge given the spillover effect in the short run; the costs may be a necessary one to enhance security in the country. The findings simply suggest that policy makers should take the spillover effect into account when devising their strategies. A more fruitful approach should be attentive to the human and geographical factors of the regions and their neighborhoods. In general, a similar strategy in areas that disfavor violence substitution is more likely to be cost-efficient and effective, as it minimizes the harm due to the likely spillover effects.

The current evaluation exercise is by no means perfect. Many qualitative studies inform us that local political context also plays an important role (e.g. Hagan et al. (2013); Long (2008)). Though some of the domestic effects are geographically limited in scope hence not likely to change the overall pattern and the argument regarding relocation and conditionality substantially, a more elaborate assessment is desirable when data of high resolution in both time and spatial dimensions are available, a task that could be challenging in a conflict-torn country. Given the scarcity of data and my research objective, which is to assess the sensitivity of previous findings to the spatial consideration, I am not able to test which of the proposed factors are generally relevant in the target selection process, nor do I provide a complete theory in explaining the variations in the results; these tasks are possible only after an empirical pattern is described and confirmed. My contribution here is more on offering a framework, a tool, and providing new empirical findings based on improved data and method for further theorization.

My findings have important implications to the recent emerging conflict diffusion literature. A basic notion of the literature is that the spread of violence is not random and directionless (Midlarsky, Crenshaw, and Yoshida, 1980). Gleditsch (2007), Buhaug and Gleditsch (2008) and Cederman et al. (2013) have advanced the research agenda and asked why conflicts cluster in space. Is the clustering a result of diffusion or attribute clustering? What are the underlying mechanisms of diffusion?[10] More recently, Checkel (2013) and Wood (2013) address the heterogeneity of diffusion mechanisms. The proposed target selection framework could be understood as a novel mechanism through which violence travels across spaces.[11] My framework integrates agency with structural characteristics: violence could be a deliberate strategy of insurgents subject to geographical constraints, be the strategy a result of the counterinsurgency efforts or not. Thus, the framework avoids the dichotomy that overwhelmingly stresses on either agency or geography.

In short, the findings in this study should bring political scientists' attention to the mobility issue and provide insights and tools that help both academicians and policy makers better address and conceptualize the target selection problem of insurgents.

[10]See also Wood (2013, 238). Braithwaite and Johnson (2012) have found evidence of clustering in the Iraqi case.

[11]See Baudains, Braithwaite, and Johnson (2013), which studies the 2011 riots in London, for a similar framework. But they hypothesized that the decision making of rioters was far from rational.

References

Angrist, J. D. and J.-S. Pischke (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Anselin, L., J. Le Gallo, and H. Jayet (2008). Spatial panel econometrics. In L. Matyas and P. Sevestre (Eds.), *The Econometrics of Panel Data*, pp. 625–660. Heidelberg: Springer.

Baltagi, B. H. (2005). *Econometric Analysis of Panel Data*. Chichester: John Wiley & Sons.

Baudains, P., A. Braithwaite, and S. D. Johnson (2013). Target choice during extreme events: A discrete spatial choice model of the 2011 London riots. *Criminology 51*(2), 251–285.

Berman, E., J. N. Shapiro, and J. H. Felter (2011). Can hearts and minds by bought? The economics of counterinsurgency in Iraq. *Journal of Political Economy 119*(4), 766–819.

Biddle, S., J. A. Friedman, and J. N. Shapiro (2012). Testing the surge: Why did violence decline in Iraq in 2007? *International Security 37*(1), 7–40.

Braithwaite, A. and S. D. Johnson (2012). Space time modeling of insurgency and counterinsurgency in Iraq. *Journal of Quantitative Criminology 28*(1), 31–48.

Brambor, T., W. R. Clark, and M. Golder (2006). Understanding interaction models: Improving empirical analyses. *Political Analysis 14*(1), 63–82.

Braumoeller, B. F. (2004). Hypothesis testing and multiplicative interaction terms. *International Organization 58*(4), 807–820.

Buhaug, H. and K. S. Gleditsch (2008). Contagion or confusion? Why conflicts cluster in space. *International Studies Quarterly 52*(2), 215–233.

Buhaug, H. and J. K. Rod (2006). Local determinants of African civil wars, 1970-2001. *Political Geography 25*(3), 315–335.

Cederman, L.-E., K. S. Gleditsch, and H. Buhaug (2013). *Inequality, Grievances, and Civil War*. Cambridge: Cambridge University Press.

Cederman, L.-E., N. B. Weidmann, and K. S. Gleditsch (2011). Horizontal inequalities ethnonationalist civil war: A global comparison. *American Political Science Review 105*(3), 478–495.

Cederman, L.-E., A. Wimmer, and B. Min (2010). Why do ethnic groups rebel? New data and analysis. *World Politics 62*(1), 87–119.

Checkel, J. T. (2013). Transnational dynamics of civil war. In J. T. Checkel (Ed.), *Transnational Dynamics of Civil War*, pp. 3–27. Cambridge: Cambridge University Press.

Crenshaw, M. (1998). The logic of terrorism terrorist behavior as a product of strategic choice. In W. Reich (Ed.), *Origins of Terrorism: Psychologies, Ideologies, Theologies, States of Mind*, pp. 7–24. Baltimore, MD: Johns Hopkins University Press.

Drake, C. J. M. (1998). The role of ideology in terrorists target selection. *Terrorism and Political Violence 10*(2), 53–85.

Elhorst, J. P. (2010). Dynamic panels with endogenous interaction effects when T is small. *Regional Science and Urban Economics 40*(5), 272–282.

Elhorst, J. P. (2012). Dynamic spatial panels: Models, methods, and inferences. *Journal of Geographical Systems 14*(1), 5–28.

Enders, W. and T. Sandler (1993). The effectiveness of antiterrorism policies: A vector-autoregression-intervention analysis. *American Political Science Review 87*(4), 829–844.

Faria, J. R. (2006). Terrorist innovations and anti-terrorist policies. *Terrorism and Political Violence 18*(1), 47–56.

Fearon, J. D. and D. D. Laitin (2003). Ethnicity, insurgency, and civil war. *American Political Science Review 97*(1), 75–90.

Franzese, Robert J., J. and J. C. Hays (2007). Spatial-econometric models of cross-sectional interdependence in political-science panel and time-series-cross-section data. *Political Analysis 15*(2), 140–164.

Franzese, Robert J., J. and J. C. Hays (2008). Interdependence in comparative politics: Substance, theory, empirics, substance. *Comparative Political Studies 41*(4/5), 742–780.

Friedman, J. A. (2011). Manpower and counterinsurgency: Empirical foundations for theory and doctrine. *Security Studies 20*(4), 556–591.

Gleditsch, K. S. (2007). Transnational dimensions of civil war. *Journal of Peace Research 44*(3), 293–309.

Goddard, S. E. (2006). Uncommon ground: Indivisible territory and the politics of legitimacy. *International Organization 60*(1), 35–68.

Greene, W. (2011). *Econometric Analysis.* Upper Saddle River, NJ: Prentice Hall.

Hagan, J., J. Kaiser, and A. Hanson (2013). Correspondence: Assessing the synergy thesis in Iraq. *International Security 37*(4), 173–181.

Hughes, G. (2010). The insurgencies in Iraq, 2003 - 2009: Origins, developments and prospects. *Defence Studies 10*(1-2), 152–176.

Humphreys, M. and J. M. Weinstein (2008). Who fights? The determinants of participation in civil war. *American Journal of Political Science 52*(2), 436–455.

Jenkins, B. (1986). Defense against terrorism. *Political Science Quarterly 101*(5), 773–786.

Lee, L.-f. and J. Yu (2010a). Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics 154*(2), 165–185.

Lee, L.-f. and J. Yu (2010b). Some recent developments in spatial panel data models. *Regional Science and Urban Economics 40*(5), 255–271.

LeSage, J. and R. K. Pace (2009). *Introduction to Spatial Econometrics.* Boca Raton, FL: CRC Press.

Lindsay, J. R. and A. G. Long (2013). Correspondence: Assessing the synergy thesis in Iraq. *International Security 37*(4), 181–189.

Long, A. G. (2008). The Anbar Awakening. *Survival 50*(2), 67–94.

Lyall, J. (2008). Are co-ethnics more effective counter-insurgents? Evidence from the Second Chechen War. *American Political Science Review 104*(1), 1–20.

Lynch, M. (2011). Explaining the Awakening: Engagement, publicity, and the transformation of Iraqi Sunni political attitudes. *Security Studies 20*(1), 36–72.

Malkasian, C. (2006). The role of perceptions and political reform in counterinsurgency: The case of western Iraq, 200405. *Small Wars & Insurgencies 17*(3), 367–394.

McCartan, L. M., A. Massell, M. Rey, and D. Rusnak (2008). The logic of terrorist target choice: An examination of Chechen rebel bombings from 1997-2003. *Studies in Conflict & Terrorism 31*(1), 60–79.

Midlarsky, M. I., M. Crenshaw, and F. Yoshida (1980). Why violence spreads: The contagion of international terrorism. *International Studies Quarterly 24*(2), 262–298.

Ord, K. (1975). Estimation methods for models of spatial interaction. *Journal of the American Statistical Association 70*(349), 120–126.

Romano, D., B. Calfano, and R. Phelps (2013). Successful and less successful interventions: Stabilizing Iraq and Afghanistan. *International Studies Perspectives. Forthcoming*.

Ross, M. (2004). What do we know about natural resources and civil war? *Journal of Peace Research 41*(3), 337–356.

Ward, M. D. and K. S. Gleditsch (2008). *Spatial Regression Models*. London: Sage Publications.

Wood, E. J. (2013). Transnational dynamics of civil war: Where do we go from here? In J. T. Checkel (Ed.), *Transnational Dynamics of Civil War*, pp. 231–258. Cambridge: Cambridge University Press.

Yu, J., R. de Long, and L.-f. Lee (2008). Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large. *Journal of Econometrics 146*(1), 118–134.

The UNU-MERIT WORKING Paper Series

2014-01 *The medium-term effect of R&D on firm growth* by Marco Capasso, Tania Treibich and Bart Verspagen

2014-02 *Diverse and uneven pathways towards transition to low carbon development: The case of diffusion of solar PV technology in China*Michiko Iizuka

2014-03 *User innovators and their influence on innovation activities of firms in Finland* by JariKuusisto, MerviNiemi and Fred Gault

2014-04 *Migration, remittances and household welfare in Ethiopia* by Lisa Andersson

2014-05 *Path-breaking directions of nanotechnology-based chemotherapy and molecular cancer therapy* by Mario Coccia and Lili Wang

2014-06 *Poor trends - The pace of poverty reduction after the Millennium Development Agenda*Richard Bluhm, Denis de Crombrugghe, Adam Szirmai

2014-07 *Firms' adoption of international standards: Evidence from the Ethiopian floriculture sector* by MuluGebreeyesu

2014-08 *School choice, segregation, and forced school closure*by Cheng Boon Ong andKristof De Witte

2014-09 *Gender difference in support for democracy in Sub-Saharan Africa: Do social institutions matter?*by MatyKonte

2014-10 *Why are women less democratic than men? Evidence from Sub-Saharan African countries* by Cecilia García-Peñalosa and MatyKonte

2014-11 *Tipping points? Ethnic composition change in Dutch big city neighbourhoods* by Cheng Boon Ong

2014-12 *Technology life cycle and specialization patterns of latecomer countries. The case of the semiconductor industry* by Giorgio Triulzi

2014-13 *Patents as quality signals? The implications for financing constraints on R&D* by Dirk Czarnitzki, Bronwyn H. Hall and Hanna Hottenrott

2014-14 *Assessment of effectiveness of Chinese aid in competence building and financing development in Sudan* by SamiaSatti Osman Mohamed Nour

2014-15 *Education, training and skill development policies in Arab Gulf countries: Macro-micro overview* by SamiaSatti Osman Mohamed Nour

2014-16 *Structure of labour market and unemployment in Sudan* by SamiaSatti Osman Mohamed Nour

2014-17 *Overview of knowledge transfer in MENA countries - The case of Egypt* by SamiaSatti Osman Mohamed Nour

2014-18 *The impact of ICT in public and private universities in Sudan*by SamiaSatti Osman Mohamed Nour

2014-19 *End-user collaboration for process innovation in services: The role of internal resources* by Mona Ashok, Rajneesh Narula and Andrea Martinez-Noya

2014-20 *Public investment and regional politics: The case of Turkey* by Mehmet Guney Celbis, Denis de Crombrugghe and Joan Muysken

2014-21 *Infrastructure and the international export performance of Turkish regions* by Mehmet Guney Celbis, Peter Nijkamp and Jacques Poot

2014-22 *Discovering and explaining work-family strategies of parents in Luxembourg* by Nevena Zhelyazkova

2014-23 *Parental leave take up and return to work of mothers in Luxembourg: An application of the model of nested dichotomies* by Nevena Zhelyazkova

2014-24 *Millennium Development Goals: Tool or token of global social governance?* by Mueid Al Raee, Elvis Amoateng, Elvis Korku Avenyo, Youssef Beshay, Mira Bierbaum, Charlotte Keijser and Rashmi Sinha

2014-25 *One Europe or several? Causes and consequences of the European stagnation* by Jan Fagerberg and Bart Verspagen

2014-26 *The harmony of programs package: Quasi-experimental evidence on deworming and canteen interventions in rural Senegal* by Théophile Azomahou, Fatoumata Diallo and Wladimir Raymond

2014-27 *Country Terms of Trade 1960-2012: Trends, unit roots, over-differencing, endogeneity, time dummies, and heterogeneity* by Thomas Ziesemer

2014-28 *The structure and comparative advantages of China's scientific research - Quantitative and qualitative perspectives* by Lili Wang

2014-29 *Transition to knowledge-based economy in Saudi Arabia* by Samia Satti Osman Mohamed Nour

2014-30 *Challenges and opportunities for transition to knowledge-based economy in Arab Gulf countries* by Samia Satti Osman Mohamed Nour

2014-31 *Migration of international students and mobilizing skills in the MENA Region* by Samia Satti Osman Mohamed Nour

2014-32 *Beyond product innovation; improving innovation policy support for SMEs in traditional industries* by René Wintjes, David Douglas, Jon Fairburn, Hugo Hollanders and Geoffrey Pugh

2014-33 *The impact of innovation support programmes on SME innovation in traditional manufacturing industries: an evaluation for seven EU regions* by Dragana Radicic, Geoffrey Pugh, Hugo Hollanders and René Wintjes

2014-34 *Beliefs dynamics in communication networks* by Théophile T. Azomahou and Daniel C. Opolot

2014-35 *Stability and strategic diffusion in networks* by Théophile T. Azomahou and Daniel C. Opolot

2014-36 *Epsilon-stability and the speed of learning in network games* by Théophile T. Azomahou and Daniel C. Opolot

2014-37 *Afghan unaccompanied minors in the Netherlands: Far away from home and protected?* by Carla Buil and Melissa Siegel

2014-38 *Multinational production and trade in an endogenous growth model with heterogeneous firms* by Hibret B. Maemir and Thomas Ziesemer

2014-39 *The political economy of research and innovation in organic photovoltaics (OPV) in different world regions* by Serdar Türkeli and René Kemp

2014-40 *Towards the societal system of innovation: The case of metropolitan areas in Europe* by Serdar Türkeli and René Wintjes

2014-41 *To return permanently or to return temporarily? Explaining migrants'* intentions by Özge Bilgili and Melissa Siegel

2014-42 *Catching up and lagging behind in a balance-of-payments-constrained dual economy* by Alejandro Lavopa

2014-43 *An introduction to the economics of rare earths* by Eva Bartekova

2014-44 *The unequal effect of India's industrial liberalization on firms' decision to innovate: Do business conditions matter?* By Maria Bas and Caroline Paunov

2014-45 *Insurgents in motion: Counterinsurgency and insurgency relocation in Iraq* by Pui-Hang Wong