ECONOMIC SHOCKS AND REBEL TACTICS*

Austin L. Wright†

May 30, 2017

Abstract

Rebel tactics vary significantly within insurgencies. I argue the local technologies of rebellion are constrained by three factors: rebel capacity, outside options, and state strength. I test the argument with microdata on rebel violence in Colombia and exploit plausibly random shocks to local income. I find evidence that economic shocks substantially affect rebel tactics. When rebel capacity increases, insurgents favor conventional tactics. Alternatively, when state strength increases and outside options improve, rebels favor irregular tactics. These results are robust to accounting for numerous potential sources of bias, including atmospheric dispersion of illicit crop herbicides, and violence spillovers from drug trafficking.

JEL Codes: D74, Q17, F16, J30, O13

*For comments, I thank Faisal Ahmed, Ryan Brutger, Anthony Fowler, Joanne Gowa, Guy Grossman, Raymond Hicks, Richard Jordan, Amanda Kennard, Ben Lessing, Saurabh Pant, Amanda Rizkallah, Tsering Shawa, Emily West, and Joseph Young. I also thank seminar and workshop participants at the following institutions: American University SIS, Chicago Harris, Connecticut College, New York University, Princeton University, University of Iowa PS/IIHR, University of Minnesota, UCLA, UC Riverside, University of Southern California SIR/SSI, and Vanderbilt University. Iván Bornacelly, Manuel Fernández, Karina Gonzalez, Daniel Mejía, Pascual Restrepo, and Luis Reyes generously shared data and the staff of *Revista Criminalidad Policía Nacional* granted access to their historical archives. John Mejía and Bob Dattore provided excellent guidance regarding historical climate data. David Thau and the Google Earth Engine program provided access to cloud-based supercomputer resources. Special debts of gratitude are owed to Ethan Bueno de Mesquita, David Carter, Oeindrilla Dube, Kris Ramsay, Jacob Shapiro, and Juan Vargas; each advanced this project significantly. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship under Grant No. 2012152169. Supporting materials are available at **www.austinlwright.com/rebel_tactics**. All errors remain my own.

†Harris School of Public Policy, The University of Chicago, 1155 East 60th Street, Chicago, Illinois 60637.

1 Introduction

Rebel tactics vary significantly *within* insurgencies. The struggle over Vietnam is a classic illustration. Viet Minh forces employed tactics that ranged from guerrilla ambushes along river trails to conventional combat. During the Battle of Dien Bien Phu, rebel forces used the hills surrounding a French encampment to launch an intense artillery attack. French military experts recommended placement of the camp at its otherwise vulnerable location because they were unaware the Viet Minh were capable of engaging in prolonged conventional attacks using anti-aircraft weapons. Up to that point in the conflict, rebels had primarily relied on guerrilla technologies of war. The rebel barrage succeeded in cutting off air resupplies to French forces, and lead to the surrender of the base and resignation of the incumbent government in France. The subsequent parliament withdrew French forces from Indochina.

Contemporary insurgencies are also characterized by a range of rebel tactics. In Nigeria, Boko Haram has used civilian victimization, village burnings, and hit-and-run attacks in areas where they have lacked the capacity to engage government forces directly. The Islamic State of Iraq and Syria (ISIS) has similarly used compulsory taxes and rents from captured oil and electricity facilities to fund sophisticated attacks on border posts and fortified police and military compounds. The Afghan Taliban—a well-established rebel organization that ruled the country until the U.S.-led invasion in 2001—still employs a variety of combat tactics. Siphoned international development aid and revenue from the lucrative opium trade in Hilmand and Kandahar have been used to finance complex attacks against foreign forces. At the same time, less capable fighters in Ghor and Kunduz have used 'shoot-and-scoot' attacks against local security forces.

Although recent research focuses how and why the technologies of rebellion differ *across* insurgencies (Kalyvas and Balcells, 2010; Bueno de Mesquita, 2013), we still know little about the conditions under which rebel tactics vary *within* conflicts, from irregular violence to conventional tactics. This is due to a tendency in current scholarship to study models of terrorism, guerrilla warfare, and conventional tactics in isolation (Findley and Young, 2012; Carter, 2015).

In this paper, I argue internal and external factors constrain when armed rebel groups produce irregular and conventional violence. I focus on three factors: rebel capacity, economic opportunities of non-combatants, and state strength. The argument yields several testable implications. When rebels are strengthened by revenue booms, they favor conventional tactics. When governments benefit from local windfalls and economic conditions improve for civilians, insurgents favor irregular tactics.

I test the argument with microdata on rebel violence and plausibly exogenous shocks to local income in Colombia. The conflict data I analyze distinguish ambush, sabotage, and hit-and-run style attacks from intentional, armed clashes between rebels and state forces (Restrepo, Spagat and Vargas, 2006). Consistent with the historical record of other insurgencies, rebel tactics in Colombia varied significantly over time and across municipalities. I analyze municipal-year data on income shocks from three outputs: coca, coffee, and oil. As cultivation of coca expands and market prices for cocaine rise, local rebel income surges, permitting subunits to better arm and recruit fighters. When coffee productivity is high and prices rise, non-combatants have economic options outside of participating in rebellion. As local oil income grows, counterinsurgent capacity increases through the allocation of royalties and tax income to fighting effort. Foreign firms also subsidize security force reallocation via cash-for-protection contracts. British Petroleum, for example, hired foreign mercenaries to train local Colombian forces put in charge of protecting their wells and pipelines (Mail and Guardian, 1997). Naturally, income shocks can also be negative, undermining rebel capacity, diminishing economic opportunities for civilians, and tempering government capacity.

I use an instrumental variables approach, leveraging plausibly exogenous variation in world prices and supply, and novel climatic data to identify shocks to local income. I highlight three results. First, negative shocks to rebel rents from coca production lead resource-constrained rebels to avoid direct engagements with state forces and employ guerrilla and terrorist tactics instead. When coca income experiences a one standard deviation gain, rebels allocate 4% more effort to conventional attacks. Second, negative shocks to local coffee income lead rebels to shift their tactics substantially. A one standard deviation decline in municipal income from coffee is associated with an 8% increase in the use of conventional tactics over irregular violence. Third, positive shocks to government revenue from oil cause insurgents shift to irregular, hit-and-run attacks on state forces. For oil income, a one standard deviation gain is associated with a 6% shift from direct engagements to indirect fighting. These results are robust to accounting for numerous potential sources of bias, including functional form and measurement assumptions, atmospheric dispersion of illicit crop herbicides, and violence spillovers from drug trafficking.

The central contribution of this paper is to examine the role of rebel capacity in shaping the technologies of rebellion. As the case of Dien Bien Phu illustrates, misunderstanding rebel capacity can lead to poor inferences about military tactics, with profound economic and political consequences. I situate rebel capacity within a framework that incorporates outside options and state strength. The conceptual argument resembles the model in Bueno de Mesquita (2013), where rebel leaders must choose to adopt conventional or irregular tactics or withdraw from conflict. Rebel tactics are influenced by the economic opportunities of civilians outside of rebel mobilization. The choice to adopt conventional tactics is increasing in rebel capacity, which is defined as the relative strength of rebel group.[1] The model, however, imposes two important restrictions. Leaders can only adopt one technology of war and this tactic is deployed uniformly by the insurgency. The argument made here recognizes that rebel leaders often strategically mix between irregular and conventional tactics and that the technologies of conflict are constrained by local dynamics, leading to tactical variation *within* the insurgency.

The econometric approach of this paper is most closely related to Dube and Vargas (2013). Dube and Vargas examine the relationship between municipal coffee and oil shocks and insurgent violence in Colombia. They find that growth in local revenue from labor intensive outputs is associated with a decline in rebel activity while gains in municipal income from capital intensive goods trigger paramilitary attacks. These findings are consistent with the opportunity cost and predation mechanisms theorized in Dal Bo and Dal Bo (2011). Yet Dube and Vargas lacks a thorough exploration of rebel capacity and does not address how the technologies of rebellion respond to exogenous shifts in the relative capabilities of insurgent and state forces.

More generally, research in economics and political science overlooks the importance of rebel capacity in shaping tactics of war. Prominent scholarship on civil conflict, including Fearon and Laitin (2003), Collier and Hoeffler (2004), Miguel, Satyanath and Sergenti (2004), Humphreys (2005) and, more recently, Bazzi and Blattman (2014), focuses on the proximate causes of civil war and the conditions under which insurgencies end. Others have more narrowly investigated armed contestation of economic assets (Le Billon, 2001; Ross, 2004; Hidalgo et al., 2010; Thies, 2010; Nielsen et al., 2011). Fjelde (2015), Jia (2014), and Vanden Eynde (2015) advance this broad agenda by investigating the relationship between subnational income shocks and political violence. Taken together, these studies offer important insights on how rents incentivize violence, yet largely neglect the mechanisms through which rent capture by insurgents influences *how* internal wars are fought, especially at a local level.

Rebel capacity remains a largely unexplored topic, in part, because gathering high quality data on rebel strength is difficult. State-of-the-art research on rebel capacity relies on slow-moving, aggregate measures of relative capabilities. One frequently used measure tracks how armed group capabilities compare with their state rivals along a five-part scale (Cunningham, Gleditsch and Salehyan, 2013; Holtermann, 2015). The limitations of this data reflect how challenging it is to reliably track rebel forces, finances, and civilian support, even at the group-year level. I leverage a well-documented fact about rebel group financing in Colombia to study rebel capacity at the microscale: rebel involvement in the Colombian drug trade

[1] The importance of state capacity is made clearer in Carter (2015).

is extensive and influences when rebels can recruit, arm, and train fighters.[2] I use newly released data to track which rebel units had access to rents from coca production, and to approximate their annual revenue stream.

This paper also contributes to political economy of development by introducing a new method for the retrospective estimation of crop production. This estimation procedure combines methodological insights from remote sensing with high resolution, historical satellite imagery to estimate the extent and intensity of drug production during periods and in locations where no such data exists. For the purposes of the present analysis, I utilize this method to estimate where and how many coca bushes were cultivated in Colombian municipalities. The solution, however, is scalable and relevant for estimating agricultural output on other contexts, such as poppy and wheat production in Afghanistan and rubber yields in Thailand. This approach holds the greatest potential value in situations where standard techniques for ground validation are not plausible, particularly in weak, insecure states with understaffed or unreliable bureaucratic institutions.[3]

In the following sections, I outline my main argument and analyze data on local economic shocks and tactical substitution by insurgents in Colombia during the height of rebel strength and reliance on drug revenue. The main results yield evidence consistent with my argument. I then introduce remote sensing measures of rebel capacity and a battery of alternative functional form and outcome specifications. The main results are robust. The final section concludes.

2 Theory & Empirical Expectations

Rebel tactics vary substantially from one region to another and as violent conflicts persist. In figure 1, I plot variation in the use of conventional and irregular tactics in 28 of Colombia's most violent municipalities. Values close to one indicate most violence in a given municipal-year were hit-and-run, ambush attacks while values close to zero indicate most rebel violence involved attacks on police stations and military outposts. Notice that rebel tactics vary significantly. In some areas at certain times, rebels primarily produce conventional tactics. In other areas in different times, they turn to irregular violence. What explains this variation? I argue that rebel tactics are constrained by three factors: the resources of their group, the strength of their state rival and the economic opportunities available to civilians outside of involvement in rebellion. These constraints can, and often do, vary at a local level.

[2] See Otis (2014) for a thorough review.

[3] The technique used in this study is of limited use in certain cases. It requires, for example, baseline data to calibrate the classification model. I discuss these details below.

At its core, the argument is simple. To produce violence, rebels need fighters and arms. Conventional violence is appealing as a means for expanding and establishing territorial control (de la Calle and Sanchez-Cuenca, 2015), but requires more fighters and arms than irregular tactics.[4] All else equal, rebels with territorial ambitions would prefer to engage in direct fighting with state forces, but engage in irregular combat when conventional tactics are not plausible.

When combatants and weapons are scarce, groups favor irregular warfare, characterized by hit-and-run attacks on state forces and, occasionally, violence against civilians. As the group's ability to field and arm fighters increases, rebels launch conventional assaults on government forces, where they engage armed combatants in coordinated, direct combat. Although rebels may allocate their entire fighting effort to irregular *or* conventional tactics, they often mix between them. The degree to which groups focus on one tactic over another is important precisely because it reflects how severely rebel capacity, state capacity, and civilian outside options constrain insurgent strategy at a local level. I clarify each of these constraints below.

Rebel capacity

Rebel organizations face resource problems that limit their ability to coordinate political activities freely or challenge state forces militarily. Resources have a multitude of potential origins. Some groups rely heavily on consensual revolutionary taxes, banditry or illegal activities like kidnapping or illicit drug production, trafficking, or protection rackets. Others are able to attract support from state sponsors, or ideologically and strategically aligned rebel groups operating in nearby conflict theaters. When rebels lack the resources to recruit, feed, and arm fighters, they are less capable of engaging in conventional fighting. Instead, they rely on irregular, hit-and-run tactics, which are less taxing to execute. Even as insurgents amass arms and expand their ranks, they may continue guerrilla attacks as they prepare for large-scale conventional engagements.

Once rebels are capable enough to pursue, establish, and defend territorial control of a region, irregular fighting, especially attacks on civilians, diminishes (Kalyvas, 2006). Resource gains may also lead to public goods provision, increasing non-combatant sympathy for the insurgency, and further consolidation of rebel control (Wood, 2003). The allocation of public goods reduces the likelihood of defection and increases the attractiveness of rebel

[4] For most organizations whose central goal is political disruption—e.g., terrorist groups—allocation of scarce resources to conventional violence is inefficient. Although territorial and non-territorial, anti-system groups face similar constraints, the former's preference for conventional violence does not necessarily apply to the latter.

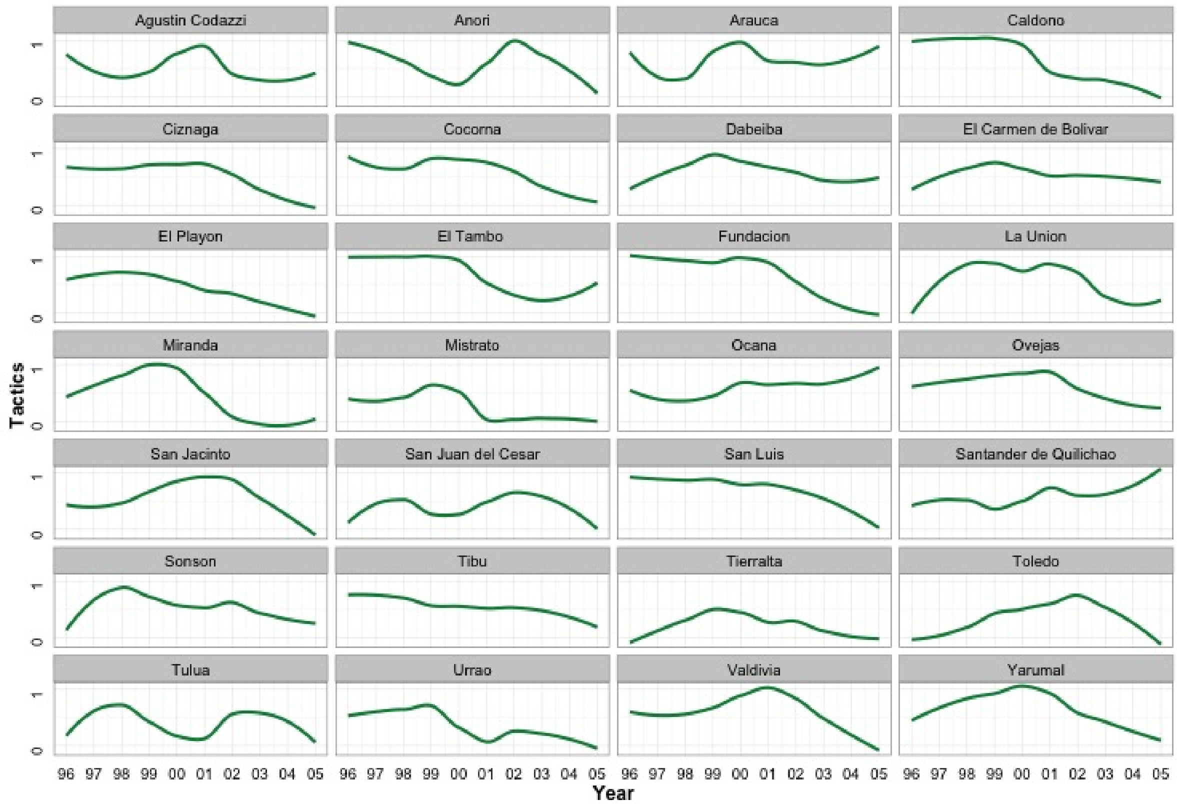


Figure 1: Shifts in tactical choice *within* an ongoing insurgency: rebel violence in Colombia, 1996-2005. Higher values (Tactics $\rightarrow$ 1) indicates relatively more irregular violence.

recruitment. The provision of private benefits such as familial trust funds—financial support allocated to family members in the event of combatant capture and detention or death—also provide a potent tool of recruitment and retention.[5] "Groups with access to economic resources are able to translate those endowments into selective incentives", Weinstein writes, "in order to motivate individuals to join the rebellion" (2007, 9). These distributional commitments are only credible when rebel groups acquire the resources and capacity to manage them. Insurgent organizations that have the means to recruit, mobilize, and support a capable fighting force, provide credible public and private goods to supporters, and establish territorial control have the classical markings of primitive states and often fight like them, engaging in direct assaults on government forces and strongholds when strategic conditions favor such tactics.

[5]Although uncommon, formal trust funds and pensions have been administered by rebel groups. The Revolutionary Armed Forces of Colombia, for example, spent roughly 2.5 million on a trust fund for captured rebels in 2003. They also provide continuing financial assistance to relatives of detained members (Saskiewicz, 1999).

While resource gains may hasten a transition from irregular to conventional tactics, unanticipated losses force rebels to reallocate scarce resources to the fighting effort. This means that weakened insurgents are likely to return to mobile, indirect engagements as well as violence against civilians (Wood, 2010, 2014). Surprise attacks, sabotage, and ambushes become more common. To stymie human and capital losses, rebels may roll back allocation of public goods or turn to violence against civilians as a means to compel compliance with requests of support (Weinstein, 2007).

- *Use of conventional tactics increases with rebel capacity.* Windfalls to rebel income and capacity lead to a relative increase in the use of conventional tactics. Alternatively, negative shocks to insurgent capacity lead to a shift from conventional to irregular tactics.

Government capacity

Government capacity figures prominently in rebel strategy. Capable governments deter rebels from direct combat by investing in counterinsurgent technologies, while weak governments are susceptible to frontal assaults. Windfalls to state dominated resources can lead to increased investment in security infrastructure. Capital-intensive sectors, like petroleum production, are immobile and often easy to tax. Positive shocks to industries that generate government revenue increase state capacity to engage in counterinsurgency campaigns. As Carter argues, "under relatively weak conditions states able to allocate resources to deter the group launching a [conventional] campaign always will do so" (2015, 12). External intervention—whether through arms transfers, foreign aid, or logistical support—can also increase a beleaguered military's capacity to neutralize internal threats.

Alternatively, where extractive industries become attractive targets of rebel capture, multinational firms may subsidize repressive capacity through side payments to military leaders and institutions. In 1995, for example, British Petroleum formally contracted the Colombian air force, military and national police to protect their top producing oil wells and transport pipelines, including earmarked funds for healthcare services, troop housing and weapons (1996; 1998; N.d.; 1995). Similarly, in 1997, Occidental Petroleum agreed to make substantial cash transfers to several Colombian military and police units in exchange for protection of their oil extraction and refinement machinery, as well as untapped oil fields (1997; 1996/1997). Occidental's military support contract explicitly set aside cash to fund a network of informants, used by the military to dismantle rebel fronts operating in areas where Occidental's financial interests were most substantial. By the late 1990s, a quarter of all Colombian army units were deployed to oil producing municipalities, with a formal mandate to repress guerrilla activity (Soltani, 2002).

A realized shift in the balance of military power towards the state makes the continued use of conventional tactics by rebels inefficient (Butler and Gates, 2009). Insurgents almost always enjoy greater force mobility than their government rivals and use of irregular tactics exploits this asymmetry to a greater degree than pitched engagements. Unlike conventional engagements, irregular tactics can be easily managed by a small number of fighters and are less susceptible to state intervention. Indeed, as Fearon observes, "in contrast to ordinary crime and conventional military confrontations, mafias and insurgencies face the problem that adding more fighters raises the risk of detection and thus capture for all existing fighters" (2007, 4). The risk of government infiltration covaries positively with state capacity (Besley and Persson, 2010). Consequently, observing a positive shock in government revenue and counterinsurgent capacity, rebels are likely to recognize conventional tactics are no longer tenable and turn to irregular warfare.

The strategic advantages gained through external support and exogenous resource booms are mirrored by the adverse consequences of aid withdrawal or loss of territorial and operational control over key economic resources (Nielsen et al., 2011; Dube and Naidu, 2015). A crumbling security infrastructure, in addition to weakening strategic capabilities, can have a demoralizing effect on military forces. Sensing the inability of military units to project or maintain control over contested areas, insurgents may allocate resources to cutting off and dismantling bases through conventional means. In areas where state forces remain intact, guerrillas rely on covert operations that target resupply convoys and other vulnerable targets.

- *Rebels resort to irregular violence as government capacity increases.* Positive shocks to government income and counterinsurgent capacity make conventional engagements unprofitable for insurgents. Relatedly, negative shocks to government capacity lead to an increased production of conventional violence on state forces.

Outside options and mobilization

The economic opportunities of civilians outside of mobilization also influence tactical choice. When non-combatants provide essential formal and informal support for rebels, insurgents are less likely to predate civilian communities and more capable of engaging state forces militarily (Weinstein, 2007). Poor economic conditions may turn the tide of the war toward rebel forces. Economic depression weakens outside options. Income from labor-intensive commodities, like coffee, are primarily distributed to plantation owners, farmers and transitory workers. Bergquist (1986) and Dube and Vargas (2013) note that contemporary coffee cultivation in Colombia is not mechanized due to environmental conditions (rugged terrain in growing areas) and relies primarily on manual labor during harvest months. The elimination of outside options to engage in profitable and productive economic activity makes mobilizing new fighters and retaining seasoned combatants easier. "In opportunity cost models", argue Bazzi and Blattman, "a civilian's incentive to rebel rises as household income and economic opportunities decline" (2014, 4). Mobilization is, by consequence, decreasing in economic opportunity (Grossman, 1991).[6] Besley and Persson (2008, 23-24) study a related model of insurgent mobilization. As rebel ranks swell and mature, leaders can more effectively (and cheaply) employ conventional tactics in direct engagements with government forces.[7]

As economic conditions improve, the reservation wage of potential insurgents increases, making recruitment more costly. This effect is likely most prominent when participation in insurgency is a full-time commitment.[8] When the opportunity costs of mobilizing or supporting rebellion are substantial, it is unlikely that insurgents will be able to field enough voluntary fighters to continue the use of conventional fighting, which is both more capital and labor intensive than irregular violence.

- *Rebels turn to irregular violence as local economic conditions improve.* Attractive outside options make mobilization of non-combatants difficult. When outside options decline, insurgents produce increased conventional violence.

3 Research Design

Collecting reliable data on rebel capacity—force levels, armaments, financial prosperity—is challenging. The difficulty of collecting fine-grained measures of capacity is why existing research analyzes relative capacity between rebel groups and their state rivals. But rebel income is rarely equally distributed within the organization, and insurgent capacity is almost always unevenly applied across contested geography. Subunits that control access points to

[6]See, also, Becker (1968) and Jayachandaran (2006).

[7]Alternatively, a dearth of outside options can also make intelligence gathering by state forces easier, since information on insurgent activity becomes less expensive to acquire from collaborators that cannot consistently profit from another occupation (Berman et al., 2011). Coordinating conventional violence exposes rebels to heightened risk of detection as well. Conventional fighting requires more fighters, support staff and armaments than irregular warfare. Each additional element required to engage state forces directly is another linkage that counterinsurgents can exploit. When economic conditions worsen, rebel units, weapon trafficking rings and communal support networks become cheaper to infiltrate. The opportunity costs of mobilization, thus, covary negatively with the risks of infiltration and detection.

[8]The distinction between full-time and part-time rebel mobilization is discussed by Mikulaschek and Shapiro (2015).

scarce resources are wealthier and more capable than fronts in the same organization that rely primarily low-level extortion. Local capacity of rebels is a consequence of locally acquired income, especially in the Colombian context.[9] If my argument is correct, local shocks to group revenue should induce microlevel variation in how rebels fight. This is not to say that macrolevel exogenous shocks do not influence rebel grand strategy, as Kalyvas and Balcells (2010) show. Instead, my claim, and the core empirical contribution of this article, is that the study of insurgent micropolitics requires data on local dynamics.

I study rebel capacity in Colombia, where rebels have relied heavily on coca cultivation, refinement and trafficking to fund their operations since the mid-1990s. Following the collapse of the cartel system, guerrilla groups, including the Revolutionary Armed Forces of Colombia (FARC) and the National Liberation Army (ELN), seized the opportunity to tax small-scale rural cultivation of coca bushes and coca paste traffickers (Lee and Thoumi, 1999; Thoumi, 2002). The FARC *Estado Mayor Central* introduced the National Financial Commission and *ayudantías* (auditors) were assigned to monitor and manage the finances of individual fronts (local subunits). The ELN instituted a similar system (2015). Although limited revenue was shared across the organization, individual fronts—which govern a handful of municipalities each—retained control over how local income was spent. Regional and U.S. interdiction of drug smugglers using light aircraft between Bolivia, Peru and Colombia, coupled with widespread eradication efforts abroad, lead to a severe reduction in regional coca exports (Angrist and Kugler, 2008). Rebels capitalized on this coca shortage by vertically integrating the coca industry: expanding domestic production networks and increasing their in-house capacity to refine leaves into coca paste and, finally, cocaine (Rangel, 2000). Using coca production to study rebel capacity requires granular data on drug cultivation. As I detail later, I study coca cultivation in two ways. First, I gather administrative data on coca eradication.[10] While reliable, these data contain known and unknown measurement error. Second, to account for these reporting errors, I develop and implement a new method for retrospective estimation of coca cultivation using high resolution satellite imagery. These data allow me to unpack the blackbox of rebel capacity in new ways.

The Colombian case is also ideal for studying local shocks to state strength and civilian opportunities outside rebellion. In Colombia, Dube and Vargas (2013) investigate plausibly random shocks to municipal-level income from coffee and oil production, induced by changes in world market prices and supply. Their study presents evidence linking income growth in coffee with increased wages and hours worked, and rising oil productivity and prices with

[9]Some rebel groups—al-Qa'ida in Iraq and the Islamic State of Iraq and Syria—maintain substantial central control over financing. In these groups, locally derived income may only partially shape capacity. For more details, see Johnston et al. (2015).

[10]For details, see Mejía and Restrepo (2014).

municipal-level capital revenue gains.[11] Variation in local income derived from coffee, thus, strongly correlates with economic opportunities outside of rebel mobilization.[12] Previous scholarship correlates oil windfalls with state weakness and failure (Auty, 1993; Ross, 2001; Ramsay, 2011). In Colombia, however, well-managed royalty institutions exist to redistribute income gains back to oil-producing municipalities and these gains substantially influence municipal wealth.[13] Local and federal agencies, in conjunction with multinational firms, have a demonstrated commitment to protecting this revenue stream from rebel capture (1998; N.d.; 1995; 1997; 1996/1997).

Coca, coffee and oil production, thus, map closely onto the theoretical argument. But income shocks to these commodities may be driven by conflict dynamics in Colombia. Following Dube and Vargas (2013), I address this concern by studying how world market prices and supply impact local income. Because Colombia is not a major producer of oil, international petroleum prices are plausibly uncorrelated with changes in domestic production, which may be associated with rebel violence. On the other hand, Colombia is a major global exporter of coffee and coca. I instrument local income growth from coffee with variation in rainfall, temperature and production intensity of the three other major coffee exporters (Brazil, Indonesia, and Vietnam). My approach to rebel income shocks is similar, but leverages original climatic data. I instrument coca income shocks in a number of ways, including panel-varying rainfall and temperature measures, soil suitability metrics, out-of-country farmgate prices, atmospheric windspeed, distance to counternarcotics airports, and production levels of other key coca exporters (Bolivia and Peru). These varied instruments are relevant, plausibly valid, and yield consistent results.

In the rest of this section, I detail data collected for this study and the identification strategy used to investigate how income shocks shape rebel tactics.

Data

Conflict

To investigate how rebel tactics vary, I study geocoded event data collected by the Conflict Analysis Resource Center (CERAC), introduced by Restrepo, Spagat and Vargas (2006). The dataset covers the Colombian conflict, from 1988 to 2005, and records more than 21,000

[11] More broadly, price slumps in labor-intensive sectors decrease demand for unskilled labor and reduce wages among employed laborers (Fjelde, 2015).

[12] Coffee production in Colombia is labor-intensive and absorbs a large number of low-skill, migratory workers during harvest months.

[13] Smith (2004), Morrison (2009), Thies (2010) present cross-national evidence that natural resources and nontax revenue may increase state capacity.

war-related events drawn from media reports and supplemented with data gathered from a network of Catholic priests. Importantly, these reports distinguish between irregular violence—ambushes, hit-and-run attacks and other indirect engagements—and conventional attacks, where rebels intentionally confront government soldiers and police officers in direct, armed combat. To clarify how irregular and conventional attacks differ, I gathered a random sample of CERAC events and mined archived copies of *Revista Noche y Niebla* to retrieve detailed event descriptions. In roughly 85% of cases, rebels initiated conventional attacks, with a limited number of formal military operations occurring during the sampled period. Conventional attacks usually involved coordinated strikes on police stations and military outposts. These events also included attempts to seize villages from government control. Acts of irregular violence typically involved ambushes on counterinsurgents traveling along jungle trails and use of cylinder bombs. Beyond violence between combatants, CERAC also records guerrilla violence against civilians.

Coffee, oil and coca

To study the impact of coffee and oil income shocks, I draw on data collected by Dube and Vargas (2013). Information on coffee cultivation is recorded by a 1997 census of coffee growers (figure 3a). Daily production of petroleum in barrels at the municipal level is available for 1988 (figure 3b). Internal coffee prices and international market prices for oil are drawn from their data archive.

I supplement these measures with data from the Colombian National Police on the extent and intensity of coca eradication (figure 3c). Publicly available data on coca cultivation in hectares is produced using both aerial photography and satellite imagery of agricultural activity from 1999-2005. An estimate of coca production at the municipal level also exists for 1994. Due to the four year gap between estimates, I primarily proxy coca leaf cultivation with the total eradicated hectares per year in each municipality.Mejía and Restrepo (2014) employ a similar technique and present evidence that the level of eradication corresponds to the intensity of cultivation. Reyes (2014) leverages exogenous variation in the patterns of eradication and confirms that anti-narcotic efforts in Colombia closely match variation in production.[14] Eradication flights were primarily limited by the operating radius of their police escorts (helicopters) as well as cloud cover, precipitation and windspeed. I review the environmental measures below. Importantly, if eradication intensity is correlated with state capacity, estimates of coca income that rely on this measure may underestimate the true

[14]Extending Reyes, I exploit several key features that influence eradication flights. I combine data on the locations of private and state-operated airports used by the Colombian Counternarcotics Police to fly eradication missions (see figure A4a) with factors that influence the feasibility of small aircraft and helicopter flight. The airports used for eradication have remained constant since the late 1980s.

causal effect of coca income on rebel tactics. Empirical support for the theoretical argument (that positive rebel revenue shocks will lead to conventional tactics) is likely the lower bound on the actual relationship.

I also gather market prices for coca and derivative products. Domestic farm-gate cocaine prices are collected from reports produced by the United Nations Office on Drugs and Crime (UNODC). These reports also detail the estimated coca leaf and cocaine exports of Bolivia and Peru, the region's other coca price-makers. I also incorporate information from a National Directorate of Coca Leaf Commercialization and Industrialization report which, with the support of UNODC, tracks monthly trends in farm-gate coca leaf prices in the Chapare region of Bolivia from 1991 to 2007 (UNODC, 2008).

Climate and environment

To identify exogenous variation in coca production, I assemble novel microdata on historical precipitation and temperature variation in Colombia. The baseline climate reanalysis was prepared by The National Centers for Environmental Prediction and Department of Energy using state-of-the-art assimilation techniques (Saha et al., 2010).[15] Monthly surface precipitation and temperature values are extracted from a .5-degree latitude by .5-degree longitude grid of earth from 1979 to 2010. These values are then converted to municipal-year measures of total rainfall, average monthly rainfall and within-year rainfall variation. All measures are area-weighted, a method Dell, Jones and Olken (2014) recommend for studying agricultural production. Similar measures of temperature fluctuations are also calculated. These covariates supplement earlier work that relied on cross-sectional variation in climatic variables (Dube and Vargas, 2013; Mejía and Restrepo, 2014). From the same source, I also collect both components of wind velocity, u and v, and calculate average monthly windspeed. Windspeed and vertical wind sheer are environmental factors that influence when small aircraft and helicopter operation are safe and feasible. Windspeed also affects the dispersion of chemical neutralizers used to deleaf coca bushes. Variation in wind velocities are studied at an atmospheric height layer relevant to both aircraft navigation and chemical dispersion (eradication).

I also address concerns regarding soil quality with geographic information from Centro de Estudios Economicos (CEDE) panel data. This source provides indices of soil erosion, soil

[15] These data are derived from reanalysis (climate modeling) of underlying meteorological data. While recent research suggests that reanalysis produces extremely accurate and precise measures of temperature variation independent of proximity to weather stations, the evidence regarding precipitation is less convincing (although it remains consistent with other surface level collection approaches) (Auffhammer et al., 2013). In Colombia, the number of reporting stations is relatively low but consistent over time. Consistency over time is important because station placement is not endogenous to the conflict.

aptitude (mineral deposits) and water accessibility. Given the agronomy of coca production, these measures of suitable growing conditions make it possible to identify, with a high level of precision, municipalities that are fertile ground for coca cultivation. Indeed, as Mejía and Restrepo (2014) assert, these indices are reliable predictors of the cross sectional location of coca crops and cultivation expansion during the period of this study.

Identification

The aim of this paper is to isolate the effect of local income shocks on tactical choice. Because insurgents can, and often do, adopt by irregular and conventional violence in the same municipal-year, we need a measure of the outcome that indicates the extent of strategic mixing across attack types. In the main analysis, the outcome of interest, $Y_{m,t}$, identifies the proportion of attacks in municipality m in year t that are irregular. This outcome indicates how much of a rebel unit's total portfolio of violence is allocated to the production irregular tactics. The violence data identify the number of irregular **attacks**, and conventional armed **clashes** between rebels, state forces and/or paramilitary groups in a given year. These event classifications correspond to similar technologies of war used in other ongoing conflicts, including Afghanistan, Iraq, the Philippines, and Syria. $Y_{m,t} = \frac{attacks}{attacks+clashes}$ during conflict years and zero otherwise. I restrict the main analysis to violence between armed combatants. As a robustness check, I include attacks on civilians as irregular violence and, separately, omit engagements between guerrilla and paramilitary units.

The measure of tactical substitution, $Y_{m,t}$, takes the value zero under two conditions: either no events have occurred in a given municipal-year or all engagements were conventional in nature. To address this inferential problem, $X_{m,t}$ includes an indicator variable that takes the value one when a municipality experiences positive levels of conflict in a given year and zero otherwise ($py_{m,t}$). This empirical strategy also implies that the coefficients of interest are calculated using only variation in tactical choice. In other words, the results presented do not address the choice between mobilizing against government forces and withdrawing from the conflict. Instead, the main analysis focuses on the tactical choice of rebels to substitute conventional warfare for irregular tactics or vice versa.

An intuitive alternative to this measure is to estimate separate coefficients for each type of violence (irregular, conventional) in levels and formally test differences across models. This approach would similarly reveal if the impact of economic shocks is distinguishable across types of violence and, if distinct, how these shocks induce strategic substitution from irregular warfare to conventional technologies and vice versa. I consider this approach, as well as a number of additional adjustments to the baseline proportional outcome, below.

The spatial fixed effects, α_m, absorb constant municipal characteristics, whether observed or unobserved, disentangling the unit-level shock from varied sources of omitted variable bias. Time fixed effects, f_t, further neutralize any common trends across municipalities in a given year. One such common shock was the presidential election of anti-FARC candidate Alavaro Uribe in 2002. Incorporating within and between constants ensures the quantity of interest is identified via localized economic shocks. I include a region-specific time trend, $\mu_r t$. This addresses concerns regarding trends (like territorial control) that vary across time by region.

As a baseline, I present OLS estimates of the relationship between economic sector values and rebel tactics in the first column of table 1. I estimate the following linear probability model:

$$\begin{aligned} Y_{m,t} = \alpha_m + f_t + \mu_r t &+ (Oil_{m,t=1988} \times O.Price_t)\beta_1 + (Coffee_{m,t=1997} \times Co.Price_t)\beta_2 \\ &+ (Coca_{m,t} \times Ca.Price_t)\beta_3 + X_{m,t}\beta_4 + \epsilon_{m,t}. \end{aligned} \tag{3.1}$$

Unless otherwise stated, all models are scaled using population weights. I use weighted estimation for two related reasons. First, the precision of the dependent variable may vary with population size. If the intensive margin of violence varies with population size (and it does), then $\epsilon_{m,t}$ is likely heteroskedastic (Solon, Haider and Wooldridge, 2015). While I correct for clustered error structures at the departmental level (a conservative approach), heteroskedasticity may continue to harm the precision of regression coefficients. Second, given the construction of the primary outcome variable, low and high intensity conflict zones where rebels allocate all effort to conventional or irregular violence obtain the same value (0 and 1 respectively) even though causal effects may be heterogeneous. Weighted estimation identifies heterogenous effects which vary by municipal population size (although not the population average effect). I return to this subject later. Yet, as Deaton (1997) and Solon, Haider and Wooldridge (2015) caution, weighted regressions may produce less precise model estimates than OLS. In table A2, panel A, I present evidence that increased precision is achieved via population scales. Although I primarily study time-varying population estimates, consistent but less precise estimates are achieved using averaged population values (table A2, panel B).

In table 1, models 1-5, I present the two stage least squares estimates of the effect of economic shocks on rebel tactics. I estimate the following model for the second stage:

$$\begin{aligned} Y_{m,t} = \alpha_m + f_t + \mu_r t &+ (Oil_{m,t=1988} \times O.Price_t)\beta_1 + (Coffee_{m,\widehat{t=1997} \times} Co.Price_t)\beta_2 \\ &+ (Coca_{m,\widehat{t \times Ca}}.Price_t)\beta_3 + X_{m,t}\beta_4 + \epsilon_{m,t}. \end{aligned} \tag{3.2}$$

This second stage analysis is primarily focused on $(Oil_{m,t=1988} \times O.Price_t)$, $(Coffee_{m,\widehat{t=1997} \times} Co.Price_t)$, and $(Coca_{m,\widehat{t \times Ca}}.Price_t)$. The coffee and coca sector values are the two endogenous regressors instrumented with $IV_{m,t}$ in the first stages. I describe these instruments in detail below and in table A1.

$$\begin{aligned}(Coffee_{m,t=1997} \times Co.Price_t), (Coca_{m,t} \times Ca.Price_t)\\ = \alpha_m + f_t + \mu_r t + (Oil_{m,t=1988} \times O.Price_t)\beta_1 + IV_{m,t}\beta_2 + X_{m,t}\beta_3 + \epsilon_{m,t},\end{aligned} \tag{3.3}$$

4 Results

In the main analysis, local income shocks are evaluated as level changes, so the interpretation of the point estimates is straightforward. Positive coefficients indicate that positive shocks are associated with irregular tactics (since irregular tactics dominate rebel strategies as the outcome variable approximates 1). Negative coefficients, however, indicate that positive shocks are associated with an increased use of conventional tactics. If the results follow the empirical expectations of the theoretical argument, coffee and oil sector growth should have **positive** coefficients (mobilization is more difficult when outside options are substantial and government capacity is high), while the coca shock variable should be **negative** (stronger rebels produce relatively more conventional violence).

In the first column of table 1, I present OLS estimates of the relationship between local income and rebel tactics. The results show that increases in local income from oil extraction deter conventional violence while increases in rebel income significantly increase the use of conventional tactics. Although slumps in coffee income are associated with increased direct assaults on government forces, this coefficient is insignificant. The estimates on coca and coffee could be downward biased, however. Intensification of clashes between rebels and government forces in agricultural areas might reduce supply, increasing international prices. For coffee, this supply effect would bias against the theorized relationship between opportunity costs and tactical choice. For coca, coefficients would trend towards zero (since supply and price effects offset as violence increases). To account for potential bias, I instrument coffee and coca income. I review the instrumental variables approach next.

Using an instrumental variables approach, presented in models 1 through 5, I find that income shocks robustly shape rebel tactics, even at a local level. In line with my argument, the coffee sector shock coefficient is positive, evidence that increased income from local coffee production causes rebels to shift to irregular tactics. When local income rises, incentives for civilians to mobilize or support rebels decline. Analogously, when coffee productivity and export prices diminish and the opportunity costs of mobilization decline, rebels produce more conventional violence. A similar relationship holds for shocks to oil income. As exports and international prices increase, rebels favor irregular violence. In oil-producing municipalities, these positive shocks lead to increased counterinsurgent capacity, through increased police activity, deployment of federal troops, and private contracts between oil-exporting firms and military units. The negative coefficient on the coca variable indicates that stronger rebels produce relatively more conventional violence. Negative shocks to rebel income, thus, have the anticipated effect of increasing the relative use of irregular, hit-and-run tactics. The magnitudes of these effects are substantial. A single deviation increase in local income from coffee is associated with an 8% shift in the portfolio of rebel violence, increasing the relative use of irregular violence. Similar increases in the value of oil and coca are associated with 6% and 4% shifts in tactical choice, respectively. These results also confirm that the OLS estimates are downward biased. For coffee, the coefficient is more than 10 times greater after instrumentation, while the substantive effect of coca income shocks is nearly three times larger with the IV approach. These differences are large and statistically significant.

In table 1 model 1, I instrument coca production using panel estimates of rainfall and temperature variation.[16] These data provide precise monthly estimates of municipal precipitation and surface climate conditions, which I aggregate to the municipal-year level. To study exogenous variation in coffee sector growth, I rely on the base instruments used by Dube and Vargas (2013). In models 2, 3 and 5, I interact my panel estimates of precipitation and temperature with a set of soil indices (water accessibility, soil erosion and soil aptitude; model 2), out-of-country farm-gate prices (model 3), and minimum linear distance to the closest counternarcotics airport (model 5).[17] Soil suitability indices provide another means of leveraging the varying agronomic conditions that favor coca but not coffee cultivation. The out-of-country coca leaf prices studied in model 3 are compiled from surveys of coca traders in Chapare region of Bolivia. Fluctuations in these farm-gate prices is driven primarily by rapid depreciation of local soil productivity during the sampled period, as well as substantial variation in the intensity of manual and aerial eradication in Cochabamba (none of which are plausibly related to municipal-level production in Colombia). The airports used for launching eradication flights, considered in model 5, remained fixed over the sample. This allows me to combine plausible exogenity in climatic conditions with fuzzy discontinuities in the fuel capacity of escort aircraft. Each set of instruments provides unique yet plausibly random variation in coca revenue. Although the first stages differ substantively in how they identify shocks to coca productivity and value, the second stage results are stable and indicate that OLS estimates undervalue the impact of rebel endowment shocks on tactical choice.

Yet there is historical evidence that insurgent groups vary tactics according to regularized

[16]For an overview of the instruments, see table A1.

[17]In table A3, I interact these climate measures with cocaine exports from Bolivia and Peru. I exclude this specification due to potential concerns regarding violations of the exclusion restriction, but the results obtained are consistent.

climatic seasons. Such concerns are particularly problematic with respect to instrumenting coca production, for which rebels may have developed an informal (and undocumented) production schedule.[18] To address these concerns, I incorporate several measures of atmospheric windspeed in model 4. I calculate monthly wind velocity averages at an atmospheric threshold that only plausibly influences tactical substitution through impacting the feasibility of small aircraft eradication flights. Importantly, crop dusting (eradication) aircraft were not equipped with weapons for offensive engagements. This instrument also produces estimates consistent with the baseline specification.

Each set of instruments is jointly strong, with no evidence of meaningful bias from overidentification. Given that my identification strategy employs as many as nine instruments to identify exogenous variation in two endogenous regressors, the standard F test would be an inappropriate benchmark for checking relevance of the instruments. As Stock and Yogo (2005) confirm, the F statistic is appropriate for models with a single endogenous regressor and a limited number of instruments (at most 3). As an alternative, I report the Cragg-Donald F statistic. The bias-minimizing critical value of this statistic for the model specifications studied in table 1 is 18.3 ($k_2 = 2$, n = 9, bias = 5%, $\alpha = .95$). The lowest observed value of this statistic is 39.43, which means the instruments are jointly strong. Using multiple instruments for each endogenous regressor can lead to biased inferences due to overidentification. To test if my instruments are strong but invalid, I calculate the Hansen statistic for all models, which yields no clear evidence of bias due to overidentification.

[insert table 1 about here]

Remote Sensing of Rebel Capacity

One of the central contributions of this paper is how I use coca income shocks to study rebel capacity. In table 1, I identify these income shocks at the municipal-year level using data on the intensity of aerial eradication. Recent research validates the claim that changes in eradication are closely associated with variation in the productivity of coca bushes (Mejía and Restrepo, 2014; Reyes, 2014). But these administrative records contain known and unknown measurement error. At the height of coca production in Colombia (2000-2002), for example, eradication figures substantially exceeded total production. Eradication was also reported in municipalities where coca production remains undocumented in archival records. Eradication figures are based on the estimated size of treated fields, as well as aircraft flight patterns, which both introduce additional noisiness to the measure.

[18]Recall, unlike opium in Afghanistan, coca has no optimal growing season in Colombia.

To address observed and potential measurement error in records of eradication activity, I develop and implement a new method for retrospective estimation of coca production. Aerial photos of coca fields were not collected between 1994-1999, which prohibits a reconstruction of production estimates using standard means. The standard remote sensing approach to estimating narcotics production combines very high resolution satellite imagery with near ground-level aerial photos of coca fields. These aerial photos represent the ground truths used to calibrate assessments of spectrum images (Verger et al., 2009, 2688-9). The process of comparing these ground truths and satellite images is labor intensive and subject to inconsistencies between coding teams. The collection of aerial photos is also a prohibitive obstacle for retrospective studies of drug production (where no such images were collected).

I sidestep this limitation by leveraging very high resolution estimates of coca production from 1999 through 2001 to validate pixel-by-pixel estimates of illicit activity. Rulinda et al. (2012, 174) implement a similar technique for benchmarking vegetative drought indices in Kenya and Tanzania. The coca production estimates this method yields are novel, and the approach is generalizable to a broad class of related agricultural studies with incomplete data. One limitation to this approach, however, is that it requires a baseline map for calibrating the classification model.[19]

I start by supplementing UNODC data on local coca production and administrative eradication estimates with greenest pixel mosaics of Colombia, from 1996 to 2005 (see figure A3). Since coca leaves have no regularized growing season, these mosaics identify the maximum vegetation productivity of each 30 meter pixel of Colombia. Coca fields are typically larger than 30 meter squares, so granularity of the pixel size should be sufficient. At this resolution, the most important validation properties tested in Verger et al. (2009, 2700-1) still hold. These mosaics are drawn from the normalized difference vegetation index (NDVI) spectrum collected by the LANDSAT 5 satellite. Images are also corrected for atmospheric anomalies.

I study NDVI values from 0 to 1, with higher values indicating greater wetness concentration. Pixels are evaluated across ten equal unit bins ($\in [0, 1]$ by .1) for each municipality on an annual basis. Traditionally, computations of this type and scale involve petabytes (millions of gigabytes) of base data. An academic partnership with Google's Earth Engine program enabled access to their cloud-based supercomputer resources.[20] I then analyze variation in the count of interval pixels in municipalities known to have produced coca in 1999, 2000 and 2001 to impute production levels between 1996 and 2005. This approach is a generalization of the stepwise multiple linear regression described in Dorigo et al. (2007, 171-2),

[19] In certain contexts, these baseline data may not exist at a sufficiently high resolution. Under certain assumptions, additional data can be collected from similar cases for calibration and utilized for projection of crop production.

[20] Google is currently accepting academic applications for this program.

with municipal estimates regressed on the entire spectral band. For municipalities m that produced coca during the study sample, I estimate the following model where t equals 1999, 2000, and 2001 sequentially.

$$\begin{aligned}\text{UNODC}-EST_{m,t} &= \alpha + (NDVI_{m,t})\beta_{1,t} + ... + (NDVI_{m,t})\beta_{10,t} + (NDVI^2_{m,t})\beta_{11,t} \\ &+ ... + (NDVI^2_{m,t})\beta_{20,t} + (Erad_{m,t})\beta_{21,t} + (Erad^2_{m,t})\beta_{22,t} + \epsilon_{m,t}.\end{aligned} \tag{4.1}$$

Using $\beta_{i,t}$, where $i \in [1, 22]$ and $t \in [1999, 2001]$, I produce within and out-of-sample predictions of coca production, $\widehat{Coca - NDVI}_{m,t}$. In areas where coca bushes were never cultivated, $\widehat{Coca - NDVI}_{m,t}$ takes the value zero. These three out-of-sample predictions vary in their consistency with observed cultivation patterns, with estimates derived from the year 2000 mosaic yielding the most precision. I retain estimated production figures from the year 1999 and 2001 mosaics as robustness checks.

In table 2, models 1 through 5, I replicate the main analysis using production values derived from the year 2000 mosaic. The findings are consistent with the main analysis in table 1 and provide further evidence of the relationship between coca windfalls and conventional fighting by rebels. When coca productivity and drug prices rise, rebels produce relatively more conventional violence against state forces. In the final two columns, I instrument variation in the predicted values of coca production using the 1999 and 2001 mosaics. Although these production estimates are marginally less precise than those derived from the year 2000 mosaic, the results again indicate that income shocks robustly shape the character of political violence in Colombia.[21]

Alternative Approaches to Tactical Choice

The main outcome variable is measured as the proportion of rebel violence in a given municipal-year classified as irregular warfare. By construction, this measure is more sensitive to variation in low-intensity areas than municipalities with a high level of violence. Because this sensitivity could bias the main results, I subject the benchmark models to a number of tests using various measures of conflict intensity as control variables. These results are presented in table 3. Models 1 through 5 yield evidence that the impact of economic shocks on tactical substitution is not driven by areas with very high or low conflict intensity.

[21] To clarify, the results presented in table 2 are estimated as follows,

$$\begin{aligned}Y_{m,t} &= \alpha_m + f_t + \mu_r t + (Oil_{m,t=1988} \times O.Price_t)\beta_1 + (\widehat{Coffee_{m,t=1997}} \times Co.Price_t)\beta_2 \\ &+ (\widehat{Coca - NDVI}_{m,t} \times Ca.Price_t)\beta_3 + X_{m,t}\beta_4 + \epsilon_{m,t}.\end{aligned} \tag{4.2}$$

In model 6, I introduce an analytic weight that exploits variation in the intensive margin of violence. These weighted regression estimates attribute greater weight to municipalities that produce more violence. Notice that increases in the substantive impact of coca and coffee shocks coincide with improved precision in the coefficient estimates.

In models 7 and 8 of table 3, I demonstrate that recoding the outcome variable by including attacks on civilians as a form of irregular warfare as well as excluding violence against paramilitary units do not change the main findings. The precision of agricultural coefficients in model 8 declines, however. This seems reasonable since paramilitary groups often acted as informal and unregulated government units during this period. I then investigate only the sample of municipalities that experienced some positive level of rebel violence conflict during the study period. Perhaps this is the more appropriate set of cases to assess. Although the relevant counterfactual changes, the model yields results in line with the full sample.

Since the outcome variable I study is a proportion, least squares may be a poor fit for the data. Although methods exist for estimating a two stage model using fractional probit and logistic models, none perform well in a difference-in-differences framework. As an alternative, I study a two stage residual inclusion model that leverages several desirable qualities of the two-limit Tobit estimator. Although ideal for this outcome, this approach is also applicable to empirical models of firm production, which involve allocating effort across a choice set of outputs.

I detail the method in the appendix A and results are presented in table 4. The two-limit model yields evidence consistent with the main specification, but indicates that the main analysis likely understates of the causal impact of resource shocks on tactical substitution.[22] While the two-limit Tobit yields substantively larger and statistically more precise estimates, I prefer the least squares specification for ease of interpretation.[23]

An alternative empirical strategy for examining tactical choice might be to separately estimate the impact of economic shocks on the production of irregular and conventional violence. The main specification measures tactical choice as a rate of substitution. This secondary approach would compare coefficients of income shocks across models of irregular and conventional attacks. This strategy has the advantage of leveraging variation in the extensive and intensive margin of insurgent activity; the decision to engage in violence, and subsequently, how much to produce. The differential rate of change across models reflects how insurgents shift tactics, from irregular to conventional technologies (or vice versa), which captures the intuition of the main specification.

[22]This difference likely obtains because population weighted regressions exploit scales to account for some but not all of the latent data generating process at the limits of the distribution.

[23]Another potential drawback to this approach is that standard diagnostic statistics are not readily available (i.e., the Cragg-Donald F statistic).

In table 5, I replicate the baseline specification and regress levels of each type of violence on economic shocks. These results are jointly estimated using seemingly unrelated two stage least squares. I then formally test whether $\beta_i^{Irregular} = \beta_i^{Conventional}$ for $i = 1, 2, 3$.[24] If the results comport with the main specification, coffee and oil coefficients in column 3 should be significantly smaller than column 2 (more negative). The coca shock coefficient, on the other hand, should be larger in column 3 relative column 2 (more positive). Turning to the results in table 5, notice that positive coffee and oil shocks induce relatively larger reductions in conventional violence compared with irregular violence (χ^2 of 65.08 [$p \approx 0.00$] and 4.67 [$p \approx 0.03$], respectively). Positive coca shocks induce relatively larger increases in conventional violence than irregular attacks (χ^2 of 7.5 [$p \approx 0.00$]). These findings should give us confidence in the main results since they yield consistent evidence using a different, and perhaps more flexible, identification strategy.

Accounting for Potential Trafficking Spillovers

Trafficking of coca through otherwise unrelated municipalities may cause conflict spillovers.[25] These spillovers may be severe enough to bias the findings in areas that experience the highest levels of drug traffic, where engagements between counterinsurgents and rebels might complicate identification of local income shocks. Although actual trafficking activity is largely unobserved, I study complex trafficking equilibria to identify municipalities that *should* experience drug traffic. I start by building a road network dataset of Colombia and gather data on rebel unit locations and drug transit points from the Colombian Ministry of Defense. I then solve a classical route optimization problem detailed by Dell (2015) and produce estimates of drug traffic intensity at the municipal level. I detail the method, data and results in the appendix B.

The optimal paths (red) are presented in figure 2. Note that some paths are darker than others, indicating the same edges are used by multiple routes. To study traffic intensity, I calculate the total length of roadways used by all paths crossing a given municipality. This value is then interacted with variation in (1) aggregate production of coca and (2) within-front production of coca. Within-front estimates are generated using a Voronoi map of rebel strongholds, presented in figure A4b (Marbate and Gupta, 2013). I incorporate these measures as exogenous covariates in the main analysis. These results are presented in table 6. Although plausible, I find no relationship between potential trafficking routes

[24] Where 1,2, and 3 represent oil, coffee, and coca shocks respectively.

[25] Conflict spillovers might also occur in municipalities through which oil passes via transit pipelines. While it is difficult to estimate flow dynamics, I consider whether conditioning on within-municipality transit pipeline length $\times$ price variation alters the main results. It does not. I thank Oleg Polivin for this point and for sharing data on pipeline fixtures.

and tactical substitution, and the main results are unchanged after conditioning on these measures.

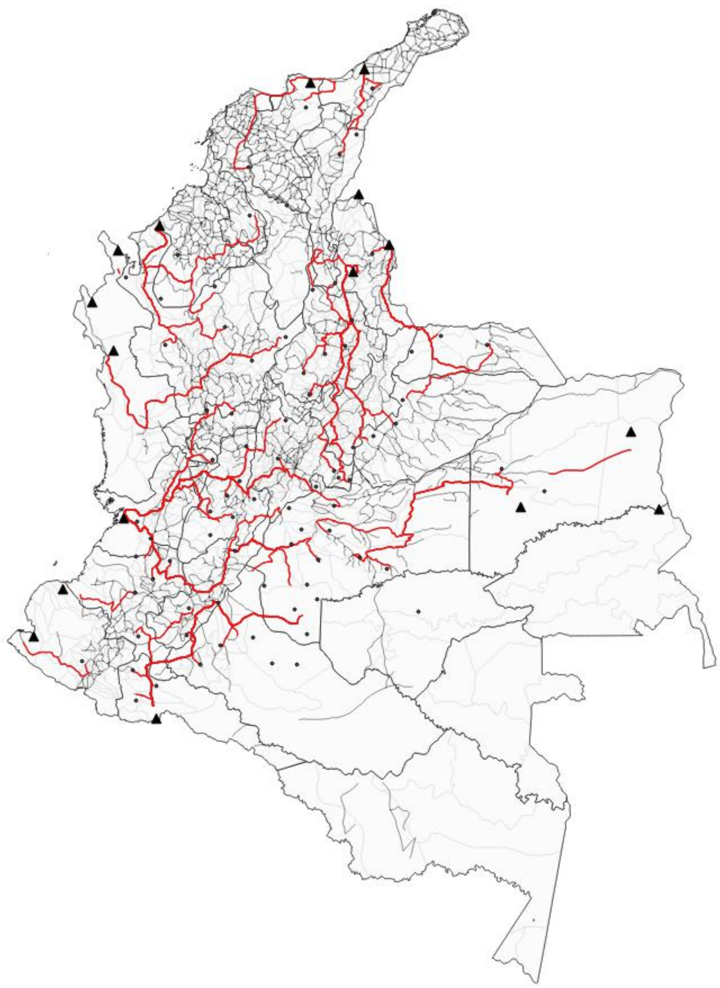


Figure 2: Road network with optimized drug trafficking routes between rebel fronts and drug transit points. Triangles indicate transit points, black dots indicate rebel front locations, and red polylines indicate optimal trafficking paths. Road segments not along these trafficking paths are dark gray.

5 Conclusion

Rebel tactics vary significantly within insurgencies. The historical record of internal conflicts over the past century provides notable examples of armed groups adopting irregular tactics in certain settings, and conventional technologies in others. Overlooking the tactical sophistication of insurgent groups can lead to faulty inferences about how they might respond to military interventions, with potentially far-reaching economic and political consequences.

I argue rebel tactics are locally constrained by three factors: rebel capacity, outside options of civilians, and state strength. Drawing on microdata from the Colombian conflict, I find robust evidence that shocks to local income substantially affect how rebels fight. Gains in rebel capacity are associated with relatively more conventional attacks, whereas increases in state capacity and outside options induce the opposite effect. These results are robust to accounting for numerous potential sources of bias, including functional form and measurement assumptions, atmospheric dispersion of illicit crop herbicides, and violence spillovers from drug trafficking.

The central contribution of this paper is highlight how rebel capacity shapes the technologies of insurgency. Existing research tends to isolate terrorism and guerrilla violence from conventional civil conflict (Tarrow, 2007). Recent studies on the economics of rebellion also primarily focus on incentives to use violence as a means of capturing economic rents, while overlooking how economic shocks influence the types of violence insurgents produce. This paper provides a more complete assessment of how the resources available to rebels alter the tactics of war, improving our understanding of the microfoundations of the political economy of conflict.

References

Angrist, Joshua and Adriana Kugler. 2008. "Rural windfall or a new resource curse? Coca, income, and civil conflict in Colombia." *Review of Economics and Statistics* 90(2):195–215.

Auffhammer, Maximilian, Solomon Hsiang, Wolfram Schlenker and Adam Sobel. 2013. "Using weather data and climate model output in economic analyses of climate change." *Review of Environmental Economics and Policy* 7(2):181–198.

Auty, Richard M. 1993. *Sustaining Development in Mineral Economics: The Resource Curse Thesis*. Routledge.

Bazzi, Samuel and Christopher Blattman. 2014. "Economic shocks and conflict: evidence from commodity prices." *American Economic Journal: Macroeconomics* 6(4):1–38.

Becker, Gary. 1968. "Crime and punishment: an economic approach." *Journal of Political Economy* 78(2):169–217.

Bergquist, Charles. 1986. *Coffee and conflict in Colombia, 1886-1910*. Duke University Press.

Berman, Eli, Michael Callen, Joseph H. Felter and Jacob N. Shapiro. 2011. "Do Working Men Rebel? Insurgency and Unemployment in Afghanistan, Iraq, and the Philippines." *Journal of Conflict Resolution* 55:496–528.

Besley, Timothy and Torsten Persson. 2008. "The incidence of civil war: theory and evidence." Working Paper 14585.

Besley, Timothy and Torsten Persson. 2010. "State capacity, conflict and development." *Econometrica* 78:1–34.

Bueno de Mesquita, Ethan. 2013. "Rebel tactics." *Journal of Political Economy* 121(2):323–357.

Butler, Christopher and Scott Gates. 2009. "Asymmetry, Parity, and (Civil) War: Can International Theories of Power Help Us Understand Civil War?" *International Interactions* 33(3):330–340.

Carter, David. 2015. "When terrorism is evidence of state success: securing the state against territorial groups." *Oxford Economic Papers* 2014 (advance access):1–17.

Collaborative agreement between BP Exploration (Colombia) and Colombian Ministry of Defense-National Army. 1995.

Collaborative agreement between Occidental de Colombia, Inc. and Colombian Ministry of Defense-NationalArmy. 1996/1997.

Collier, Paul and Anke Hoeffler. 2004. "Greed and grievance in civil war." *Oxford Economic Papers* 56(563-595).

Colombia: Human Rights Concerns Raised By The Security Arrangements of Transnational Oil Companies. 1998.

Crime, InSight. 2015. "ELN.".
URL: *http://www.insightcrime.org/colombia-organized-crime-news/eln-profile*

Cunningham, David E., Kristian Skrede Gleditsch and Idean Salehyan. 2013. "Non-state actors in civil wars: A new dataset." *Conflict Management and Peace Science* 30(5):515–531.

Dal Bo, Ernesto and Pedro Dal Bo. 2011. "Workers, Warriors, and Criminals: Social Conflict in General Equilibrium." *Journal of the European Economic Association* 9(4):646–677.
URL: *http://dx.doi.org/10.1111/j.1542-4774.2011.01025.x*

de la Calle, Luis and Ignacio Sanchez-Cuenca. 2015. "How Armed Groups Fight: Territorial Control and Violent Tactics." *Studies in Conflict and Terrorism* 0:1–19.

Deaton, Angus. 1997. *The analysis of Household Surveys: A Microeconomic Approach to Development Policy*. World Bank.

Dell, Melissa. 2015. "Trafficking Networks and the Meixcan Drug War." *The American Economic Review* 105(6):1738–79.

Dell, Melissa, Benjamin Jones and Benjamin Olken. 2014. "What do we learn from the weather? The new climate-economy literature." *Journal of Economic Literature* 52(3):740–798.

Dorigo, W. A., R. Zurita-Milla, A. J. W. de Wit, J. Brazile, R. Singh and M. E. Schaepman. 2007. "A review on reflective remote sensing and data assimilation techniques for enhanced agroecosystem modeling." *International Journal of Applied Earth Observation and Geoinformation* 9:165–193.

Dube, Oeindrila and Suresh Naidu. 2015. "Bases, Bullets, and Ballots: The Effect of US Military Aid on Political Conflict in Colombia." *The Journal of Politics* 77(1):249–267.

Dube, Oeindrilla and Juan Vargas. 2013. "Commodity price shocks and civil conflict: evidence from Colombia." *Review of Economic Studies* 80:1384–1421.

Fearon, James. 2007. *Institutions and economic performance*. Harvard University Press chapter Economic development, insurgency and civil war.

Fearon, James and David Laitin. 2003. "Ethnicity, insurgency and civil war." *American Political Science Review* 97(1):75–90.

Findley, Michael G. and Joseph K. Young. 2012. "Terrorism and Civil War: A Spatial and Temporal Approach to a Conceptual Problem." *Perspectives on Politics* 10(2):285.

Fjelde, Hanne. 2015. "Farming or Fighting? Agricultural Price Shocks and Civil War in Africa." *World Development* 67:525–534.

Grossman, Herschel. 1991. “A general equilibrium model of insurrection.” *American Economic Review* 81(912-921).

Hidalgo, Daniel, Suresh Naidu, Simeon Nichter and Neal Richardson. 2010. “Economic determinants of land invasions.” *Review of Economics and Statistics* 92(3):505–523.

Holtermann, Helge. 2015. “Relative Capacity and the Spread of Rebellion: Insights from Nepal.” *Journal of Conflict Resolution* pp. 1–29.

Human Rights Watch interview with Stephen T. Newton, president of Occidental de Colombia, Inc. 1997.

Humphreys, Macartan. 2005. “Natural resources, conflict and conflict resolution: uncovering the mechanisms.” *Journal of Conflict Resolution* 49(4):508–537.

Jayachandaran, Seema. 2006. “Selling labor low: wage responses to productivity shocks in developing countries.” *Journal of Political Economy* 114(3):538–575.

Jia, Ruixue. 2014. “Weather shocks, sweet potatoes and peasant revolts in historical China.” *The Economic Journal* pp. 92–118.

Johnston, Patrick, Howard Shatz, Danielle Jung and Jacob N. Shapiro. 2015. “Foundations of the Islamic State: Management, Money, and Terror in Iraq.”.

Kalyvas, Stathis. 2006. *The logic of violence in civil war.* Cambridge University Press.

Kalyvas, Stathis and Laia Balcells. 2010. “International System and Technologies of Rebellion: How the End of the Cold War Shaped Internal Conflict.” *American Political Science Review* 104(3):415–429.

Le Billon, Philippe. 2001. “The Political Ecology of War: Natural Resources and Armed Conflict.” *Political Geography* 20:561–584.

Lee, Rensselaer W. and Francisco E. Thoumi. 1999. “The criminal-political nexus in Colombia.” *Trends in Organized Crime* 5(2).

Mail and Guardian. 1997. “BP’s secret soldiers.” *The Mail and Guardian Newspaper* .

Marbate, Punam and Reetu Gupta. 2013. “Fortune’s Method: An Efficient Method for Voronoi Diagram Construction.” *International Journal of Advanced Research in Computer and Communication Engineering* 2(12):4808–4814.

Mejía, Daniel and Pascual Restrepo. 2014. “Bushes and bullets: illegal cocaine markets and violence in Colombia.” Working paper.

Miguel, Edward, Shanker Satyanath and Ernest Sergenti. 2004. “Economic shocks and civil conflict: an instrumental variables approach.” *Journal of Political Economy* 112(4):725–753.

Mikulaschek, Christoph and Jacob N. Shapiro. 2015. "Lessons from America's post-9/11 Wars.".

Morrison, Kevin M. 2009. "Oil, Nontax Revenue, and the Redistributional Foundations of Regime Stability." *International Organization* 63(1):107–138.

Nielsen, Richard A., Michael G. Findley, Zachary S. Davis, Tara Candland and Daniel L. Nielson. 2011. "Foreign aid shocks as a cause of violent armed conflict." *American Journal of Political Science* 55(2):219–232.

Oil Companies Buying an Army To Ward Off Rebels in Colombia. 1996.

Otis, John. 2014. The FARC and Colombia's Illegal Drug Trade. Technical report Wilson Center: Latin American Program.

Petroleum, British. N.d. "BP in Colombia:a refutation of recent allegations (company document).".

Ramsay, Kristopher. 2011. "Revisiting the Resource Curse: Natural Disasters, the Price of Oil, and Democracy." *International Organization* 65(3):507–529.

Rangel, Alfredo. 2000. "Paraistes and predators: guerrillas and the insurection economy of Colombia." *Journal of International Affairs* (577-601).

Restrepo, Jorge, Michael Spagat and Juan Vargas. 2006. "The Severeity of the Colombian Conflict: Cross-Country Datasets Versus New Micro-Data." *Journal of Peace Research* 43:99–115.

Reyes, Luis. 2014. "Estimating the causal effect of forced eradication on coca cultivation in Colombian municipalities." *World Development* 61:70–84.

Ross, Michael. 2004. "What do we know about natural resources and civil war?" *Journal of Peace Research* 41:337–356.

Ross, Michael L. 2001. "Does Oil Hinder Democracy?" *World Politics* 53(3):325–361.

Rulinda, C. M., A. Dilo, W. Bijker and A. Stein. 2012. "Characterising and quantifying vegetative drought in East Africa using fuzzy modelling and NDVI data." *Journal of Arid Environments* 78(169-178).

Saha, Suranjana, Shrinivas Moorthi, Hua-Lu Pan, Xingren Wu, Jiande Wang, Sudhir Nadiga, Patrick Tripp, Robert Kistler, John Woollen, David Behringer, Haixia Liu, Diane Stokes, Robert Grumbine, George Gayno, Jun Wang, Yu-Tai Hou, Hui-Ya Chuang, Hann-Ming H. Juang, Joe Sela, Mark Iredell, Russ Treadon, Daryl Kleist, Paul Van Delst, Dennis Keyser, John Derber, Michael Ek, Jesse Meng, Helin Wei, Rongqian Yang, Stephen Lord, Huug Van Den Dool, Arun Kumar, Wanqiu Wang, Craig Long, Muthuvel Chelliah, Yan Xue, Boyin Huang, Jae-Kyung Schemm, Wesley Ebisuzaki, Roger Lin, Pingping Xie, Mingyue Chen, Shuntai Zhou, Wayne Higgins, Cheng-Zhi Zou, Quanhua Liu, Yong Chen, Yong Han, Lidia Cucurull, Richard W. Reynolds, Glenn Rutledge and Mitch Goldberg. 2010.

"The NCEP climate forecast system reanalysis." *Bulletin of the American Meteorological Society* 91(8):1015–1057.

Saskiewicz, Paul E. 1999. *The Revolutionary Armed Forces of Colombia - People's Army (FARC-EP): Marxist-Leninist insurgency or criminal enterprise?* Naval Postgraduate School.

Smith, Benjamin. 2004. "Oil Wealth and Regime Survival in the Developing World." *American Journal of Political Science* 48(2):232–246.

Solon, Gary, Steven J. Haider and Jeffrey M. Wooldridge. 2015. "What are we weighting for?" *The Journal of Human Resources* 50(2):301–316.

Soltani, Atossa, ed. 2002. *Bush Reveals the Crude Nature of US Colombia Policy by Proposing Military Protection for OXY Plan Will Only Fuel Civil Strife in Colombia*. Amazon Watch.

Stock, James and Motohiro Yogo. 2005. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*. Cambridge University Press chapter Testing for Weak Instruments in Linear IV Regression.

Tarrow, Sidney T. 2007. "Inside insurgencies: Politics and violence in an age of civil war." *Perspectives on Politics* 5(3):587–600.

Terza, Joseph V., Anirban Basu and Paul J. Rathouz. 2008. "Two-Stage Residual Inclusion Estimation: Addressing Endogeneity in Health Econometric Modeling." *Journal of Health Economics* 27(3):531–543.

Thies, Cameron. 2010. "Of Rulers, Rebels and Revenue: State Capacity, Civil War Onset and Primary Commodities." *Journal of Peace Research* 47(3):321–332.

Thoumi, Francisco E. 2002. "Illegal drugs in Colombia: from illegal economic boom to social crisis." *Annals of the American Academy of Political and Social Science* 582:102–116.

UNODC. 2008. *Coca cultivation in the Andean region: a survey of Bolivia, Colombia and Peru*. United Nations Office on Drugs and Crime.

Vanden Eynde, Oliver. 2015. Targets of violence: evidence from India's Naxalite conflict. Technical report Paris School of Economics.

Verger, A., B. Martínez, F. Camacho-De Coca and F. J. García-Haro. 2009. "Accuracy assessment of fraction of vegetation cover and leaf area index estimates from pragmatic methods in a cropland area." *International Journal of Remote Sensing* 30(10):2685–2704.

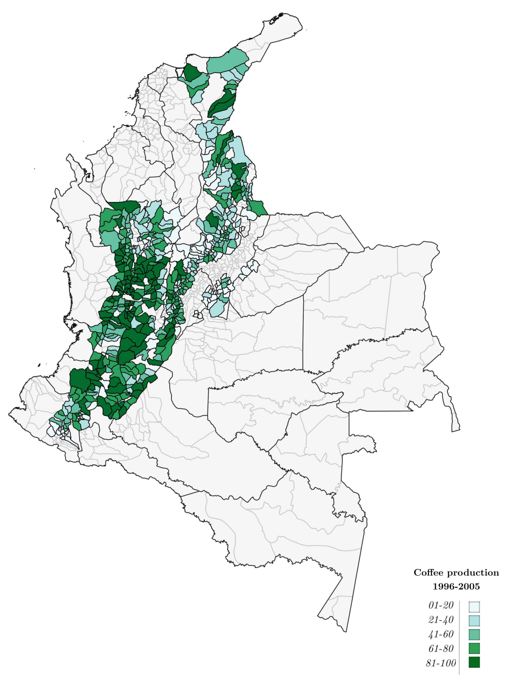
Weinstein, Jeremy. 2007. *Inside rebellion: the politics of insurgent violence*. Cambridge University Press.

Wood, Elisabeth J. 2003. *Insurgent Collective Action and Civil War in Elsalvador*. Cambridge University Press.

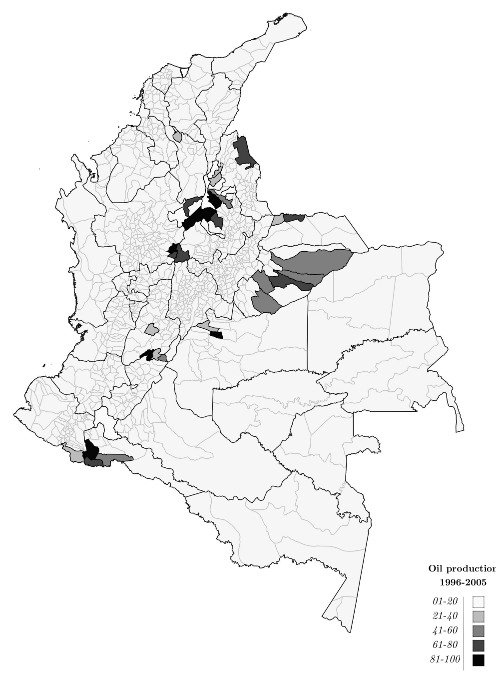
Wood, Reed M. 2010. "Rebel Capability and Strategic Violence against Civilians." *Journal of Peace Research* 47(5):601–614.

Wood, Reed M. 2014. "From Loss to Looting? Battlefield Costs and Rebel Incentives for Violence." *International Organization* 68(4):979–999.

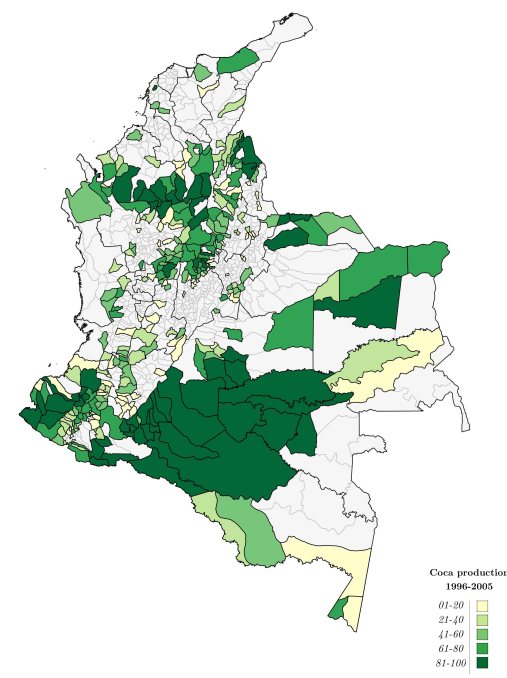
Wooldridge, Jeffrey M. 2013. *Econometric analysis of cros section and panel data.* The MIT Press.



(a) Coffee production



(b) Oil production



(c) Coca production (eradication intensity)

Figure 3: Variation in oil, coffee and coca production, 1996-2005 averages

Table 1: OLS and instrumental variables estimation of the effect of economic shocks on rebel tactics

	OLS estimates	(1) base + climate	(2) base + rainfall × soil indices	(3) base + rainfall × Chapare prices	(4) base + climate + windspeed	(5) base + climate + dist. to airport
Coffee sector shock	0.00828	0.103*	0.105*	0.0653*	0.0822$^{\gamma}$	0.103*
	(0.0175)	(0.0517)	(0.0522)	(0.0314)	(0.0450)	(0.0475)
Coca sector shock	-0.00116*	-0.00335*	-0.00376*	-0.00384*	-0.00318*	-0.00334*
	(0.000457)	(0.00161)	(0.00173)	(0.00174)	(0.00159)	(0.00158)
Oil sector shock	0.249***	0.248***	0.248***	0.252***	0.249***	0.248***
	(0.0509)	(0.0404)	(0.0388)	(0.0354)	(0.0396)	(0.0409)
Diagnostics						
C-D F statistic		58.63	57.19	56.26	39.43	42.49
Hansen statistic		4.272	3.324	3.536	7.135	6.271
Hansen p-value		0.370	0.505	0.618	0.415	0.508
Coffee sector (first stage)	-					
AP F statistic		4.528	5.152	5.454	7.393	3.683
AP p-value		0.00325	0.00158	0.000602	0.0000211	0.00399
Coca sector (first stage)	-					
AP F statistic		2.957	2.658	2.555	2.657	5.710
AP p-value		0.0270	0.0419	0.0397	0.0247	0.000171
N	9680	9680	9530	9680	9660	9680

Dependent variable is $\frac{attacks}{attacks+clashes}$. Municipality fixed effects, year fixed effects, log of population and linear trends by region are omitted. The coffee sector value is instrumented using the product of cumulative coffee export volume of three major producers (Brazil, Vietnam, and Indonesia) and rainfall variation, price-maker exports interacted with temperature trends and the product of cubic rainfall volume, temperature and major exporter production. The coca sector value is identified using municipality estimates of coca bush eradication, interacted with internal prices. The sequence of first stage instruments is introduced in table A1.

- Clustered standard errors in parentheses, department.

$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Retrospective estimation of coca production using year 2000 mosaic, with supplemental year 1999 and 2001 measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coffee sector shock	0.0807*	0.0762*	0.0508	0.0736*	0.0857*	0.0800*	0.0736*
	(0.0367)	(0.0350)	(0.0313)	(0.0339)	(0.0392)	(0.0357)	(0.0324)
Coca sector shock (remote sensing; 2000 base)	-0.0331**	-0.0329**	-0.0317**	-0.0335**	-0.0330**		
	(0.0105)	(0.0103)	(0.0108)	(0.0106)	(0.0102)		
Coca sector shock (1999 base)						-0.0489$^{\gamma}$	
						(0.0292)	
Coca sector shock (2001 base)							-0.0387**
							(0.0123)
Oil sector shock	0.257***	0.258***	0.260***	0.258***	0.257***	0.294***	0.257***
	(0.0633)	(0.0629)	(0.0607)	(0.0623)	(0.0640)	(0.0611)	(0.0748)
Diagnostics							
C-D F statistic	90.94	87.03	135.8	68.35	67.98	31.18	31.44
Hansen statistic	5.270	2.373	2.929	8.107	8.944	3.881	4.021
Hansen p-value	0.384	0.795	0.818	0.423	0.347	0.693	0.674
N	8768	8768	8768	8768	8768	8768	8768

Dependent variable is $\frac{attacks}{attacks+clashes}$. Municipality fixed effects, year fixed effects, log of population and linear trends by region are omitted.

- Clustered standard errors in parentheses, department.

$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Impact of economic shocks on tactics adjusting for various measures/weights of conflict intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Coffee sector shock	0.0571$^{\gamma}$	0.0607*	0.0637*	0.0656*	0.0647*	0.122**	0.0581*	0.0602$^{\gamma}$	0.0735*
	(0.0303)	(0.0297)	(0.0308)	(0.0306)	(0.0302)	(0.0385)	(0.0283)	(0.0321)	(0.0337)
Coca sector shock	-0.00420*	-0.00388*	-0.00384*	-0.00385*	-0.00383*	-0.00728**	-0.00334$^{\gamma}$	-0.00301$^{\gamma}$	-0.00439*
	(0.00177)	(0.00177)	(0.00173)	(0.00176)	(0.00176)	(0.00266)	(0.00201)	(0.00180)	(0.00223)
Oil sector shock	0.253***	0.259***	0.259***	0.252***	0.254***	0.248**	0.276***	0.273***	0.254***
	(0.0458)	(0.0441)	(0.0408)	(0.0374)	(0.0396)	(0.0823)	(0.0304)	(0.0269)	(0.0356)
Intensity measures	✓	✓	✓	✓	✓	-	-	-	-
Intensity weighted estimation	-	-	-	-	-	✓	-	-	-
Alternative outcome measure	-	-	-	-	-	-	include	exclude	-
	-	-	-	-	-	-	non-combat.	paramil.	-
Alternative subset	-	-	-	-	-	-	-	-	only units
	-	-	-	-	-	-	-	-	w/ + viol.
Number of conflict events	-0.00628$^{\gamma}$								
	(0.00363)								
ln(Number of conflict events)		-0.0247							
		(0.0252)							
One event			0.0228						
			(0.0323)						
Two or fewer				-0.00200					
				(0.0187)					
Three or fewer					0.00431				
					(0.0248)				
Diagnostics									
C-D F statistic	57.47	56.71	56.31	56.04	56.14	31.67	56.30	56.24	42.09
Hansen statistic	3.517	3.546	3.522	3.549	3.549	4.116	5.471	3.200	7.104
Hansen p-value	0.621	0.616	0.620	0.616	0.616	0.533	0.361	0.669	0.213
N	9680	9680	9680	9680	9680	9680	9680	9680	6955

Dependent variable is $\frac{attacks}{attacks+clashes}$. Municipality fixed effects, year fixed effects, log of population and linear trends by region are omitted.
- Clustered standard errors in parentheses, department.
$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Evaluating impact of economic shocks on tactics using two-limit Tobit model

	(1)	(2)	(3)	(4)	(5)
Coffee sector shock	0.565***	0.576***	0.218***	0.495***	0.580***
	(0.00514)	(0.00519)	(0.00523)	(0.00518)	(0.00518)
Coca sector shock	-0.0149***	-0.0181***	-0.0147***	-0.0129***	-0.0118***
	(0.000276)	(0.000277)	(0.000267)	(0.000276)	(0.000277)
Oil sector shock	0.646***	0.654***	0.673***	0.647***	0.642***
	(0.00464)	(0.00467)	(0.00464)	(0.00464)	(0.00464)
N	9680	9530	9680	9660	9680

Dependent variable is $\frac{attacks}{attacks+clashes}$. Municipality fixed effects, year fixed effects, log of population and linear trends by region are omitted. Instruments are noted in the overview of table 1.
- Clustered standard errors in parentheses, department.
$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Impact of economic shocks on tactics measured in levels rather than rate

	(1)	(2)	(3)	
	Main specification: rate	Main specification: levels		Differences Test
	-	Irregular	Conventional	(1) - (3)
Coffee sector shock	0.109*	-0.124***	-0.538***	65.08
	(0.0554)	(0.0368)	(0.0428)	p-val = 0.000
Coca sector shock	-0.00413***	-0.0000380	0.0104***	17.50
	(0.000848)	(0.00181)	(0.00211)	p-val = 0.000
Oil sector shock	0.250***	0.240	-0.900*	4.67
	(0.0387)	(0.379)	(0.441)	p-val = 0.0308
Diagnostics				
C-D F statistic	162.2	162.1	162.1	-
Hansen statistic	1.353	0.877	4.622	-
Hansen p-value	0.508	0.645	0.0992	-
N	9680	9680	9680	-

Dependent variable in Column 1 is $\frac{attacks}{attacks+clashes}$. Column 2 is attacks in levels. Column 3 is clashes in levels. Coefficient tests are reported between levels models. Columns 2 and 3 are seeming unrelated 2SLS estimates which account for potential dependence across models (omitting the peace-year indicator variable). Instrument is maximum productivity × Chapare prices. Municipality fixed effects, year fixed effects, log of population and linear trends by region are omitted.
- Clustered standard errors in parentheses, department.
$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Baseline results including network analysis measure of coca trafficking

	(1)	(2)
Coffee sector shock	0.0655*	0.0655*
	(0.0314)	(0.0315)
Coca sector shock	-0.00386*	-0.00380*
	(0.00174)	(0.00182)
Oil sector shock	0.252***	0.253***
	(0.0353)	(0.0352)
Trafficking network × nat'l prod.	1.17e-13	
	(5.33e-13)	
Trafficking network × reg'l prod.		1.55e-09
		(2.91e-09)
Diagnostics		
C-D F statistic	56.28	52.64
Hansen statistic	3.548	3.604
Hansen p-value	0.616	0.608
N	9680	9680

Dependent variable is $\frac{attacks}{attacks+clashes}$. Municipality fixed effects, year fixed effects, log of population and linear trends by region are omitted.
- Clustered standard errors in parentheses, department.
$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Summary statistics

Variable	Mean	Std. Dev.	N
Panel variables			
Guerrilla attacks on government forces (irregular)	0.383	1.204	9680
Guerrilla clashes with government forces (conventional)	0.427	1.417	9680
Tactical substitution	0.136	0.316	9680
Log eradication coca, hectares	0.353	1.405	9680
Rainfall (reanalysis monthly average), MM	0.329	0.291	9680
Temperature (reanalysis monthly average), K	288.232	14.234	9680
Windspeed (reanalysis monthly average), KM/hour	1.409	0.608	9660
Log population, millions	-4.342	0.972	9680
Municipal variables			
Oil production, hundred thousand barrels per day (1988)	0.003	0.054	968
Coffee production, thousands of hectares (1997)	0.830	1.535	968
Rainfall volume annual total, cm^3 (precise estimate)	1856.373	974.628	968
Temperature, celsius (precise estimate)	21.325	4.99	968
Water accessibility index	$3303.66e3$	$537.03e3$	953
Soil erosion index	1.95	1.058	953
Soil suitability index	2.664	1.201	953
Minimum distance to counter-narcotics airport, linear KM	124.409	78.305	968
Annual variables			
Log internal market coffee price, thousands of 2006 pesos per pound	0.524	0.224	10
Log global oil price, thousands of 2006 pesos per barrel	4.245	0.454	10
Log internal market cocaine price, pesos per KG	8.037	0.386	10
Log Chapare market (farm-gate) coca price, US dollars per KG	9.907	5.187	10
Log coffee price-maker production, millions of 60 KG bags	3.61	0.215	10

Online Appendices

Table of Contents

Figures

Tables

A An alternative two stage approach

Since I study mixing between two strategies, the outcome of interest — tactical substitution — is bounded by zero and one. It is known that ordinary least squares may produce estimates of the dependent variable outside the unit interval. To address this concern, I develop a fractional response two stage model. To do this, I estimate a set of linear first stage models that replicate the single step method employed in the main analysis and extract residuals. I then include these residuals in a second stage, along with the endogenous regressors. In the linear case, this two stage residual inclusion (2SRI) method is equivalent to 2SLS. When the outcome variable is non-linear (e.g., binary or fractional response), 2SRI is more consistent than two stage non-linear least squares (Terza, Basu and Rathouz, 2008, 536-537).

Although fractional specifications of two stage probit and logistic models exist, neither perform well in a panel difference-in-differences framework. If, however, the distribution of the outcome variable piles up at each corner of the unit interval, a latent variable analysis is consistent and unbiased. This approach is analogous to truncation of the dependent variable, where variation is only observed above and below thresholds determined by an underlying data generating process. In the present study, the data generating process at each corner of the distribution is straightforward. Rebels can allocate up to their maximum capacity in any given period. Although capacity may vary from unit to unit or within units over time, allocation of *all* fighting effort to irregular or conventional engagements obtains the same value along the outcome variable independent of rebel capacity (either zero in the case of conventional fighting or one, when insurgents focus solely on irregular violence). The impact of resource shocks on tactical substitution, therefore, is truncated. The main analysis addresses this concern indirectly through population weights, which covary with the degree of unobserved censoring on the dependent variable. This approach likely produces underestimates of the quantities of interest, however.

Even if we indirectly adjust for truncation of the outcome, the potential bias of OLS estimates remains. I address this concern by exploiting several desirable properties of a two-limit Tobit model in the second stage. Most importantly, a two-limit Tobit adjusts estimates with respect to the probability of being within the limits of the latent variable (the likelihood of observing a value strictly between zero and one). Following Wooldridge (2013), let L_1 and L_2 define the two limits of y, the outcome variable. Define the latent variable y' as $\mathbf{x}\beta + u$, such that u, conditional on $\mathbf{x}$, follows a normal distribution. Where y' is less than or equal to L_1, let the outcome variable equal the lower threshold. If y' is greater than or equal to the upper limit, let y equal L_2. Extending the one-limit Tobit, let values between the limits coincide with the latent quantity, so $y = y$' when y' is greater than to L_1 and less than L_2.

Consequently, the two-limit estimate is only appropriate when the probability of observing values at both limits is non-zero. The measure of tactical substitution studied in the main analysis (figure A1a), as well as alternative measures including non-combatant attacks (figure A1b) and excluding paramilitary violence (figure A1c), follows this bimodal pile-up at each tail with a (roughly) continuous distribution within the limits. What's more, the log likelihood of this approach is well-behaved and standard asymptotic theory follows maximum likelihood estimation, even within a difference-in-differences framework leveraging analytic weights and clustered error structures. Although this model is particularly appropriate for the present analysis, related work on the empirical implications of theoretical bargaining models may profit from it's application.

To clarify, I implement separate models in the first stage,

$$
\begin{aligned}
(Coffee_{m,t=1997} \times Co.Price_t) \\
&= \alpha_m + f_t + \mu_r t + (Oil_{m,t=1988} \times O.Price_t)\beta_1 \\
&\quad + IV_{m,t}\beta_2 + X_{m,t}\beta_3 + \epsilon_{m,t},
\end{aligned} \tag{A.1}
$$

$$
\begin{aligned}
(Coca_{m,t} \times Ca.Price_t) \\
&= \alpha_m + f_t + \mu_r t + (Oil_{m,t=1988} \times O.Price_t)\beta_1 \\
&\quad + IV_{m,t}\beta_2 + X_{m,t}\beta_3 + \epsilon_{m,t},
\end{aligned} \tag{A.2}
$$

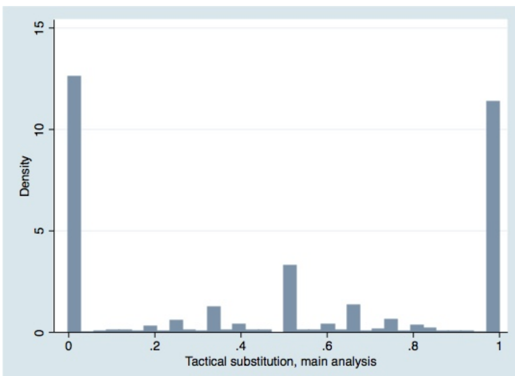
where $IV_{m,t}$ is a vector of exogenous instruments that varies according to each model and described in the overview of instrumental variables above.[26] I then identify the unexplained variation in $(Coffee_{m,t=1997} \times Co.Price_t)$ and $(Coca_{m,t} \times Ca.Price_t)$, labelling the residuals as r_{co} and r_{ca} respectively. I then incorporate these residuals in a second stage model (of tactical substitution), with lower and upper lower limits following the discussion above,

$$
\begin{aligned}
Y_{m,t} &= \alpha_m + f_t + \mu_r t + (Oil_{m,t=1988} \times O.Price_t)\beta_1 \\
&\quad + (Coffee_{m,t=1997} \times Co.Price_t)\beta_2 + r_{co} \\
&\quad + (Coca_{m,t} \times Ca.Price_t)\beta_3 + r_{ca} + X_{m,t}\beta_4 + \epsilon_{m,t}, \text{ such that } 0 < Y_{m,t} < 1.
\end{aligned} \tag{A.3}
$$

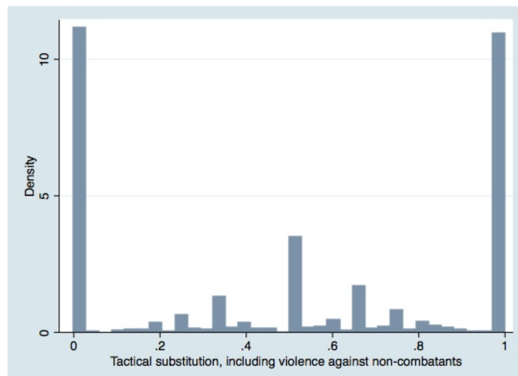
This second stage analysis is primarily focused on $(Oil_{m,t=1988} \times O.Price_t)$, $(Coffee_{m,t=1997} \times Co.Price_t)$, and $(Coca_{m,t} \times Ca.Price_t)$. Recall $(Coffee_{m,t=1997} \times Co.Price_t)$ and $(Coca_{m,t} \times Ca.Price_t)$ in the presence of r_{co} and r_{ca} are equivalent to $\widehat{(Coffee_{m,t=1997} \times Co.Price_t)}\beta_2$ and $\widehat{(Coca_{m,t} \times Ca.Price_t)}\beta_3$ in equation (3.2).

The estimates derived from this model are presented in table 4 and discussed in the main text.

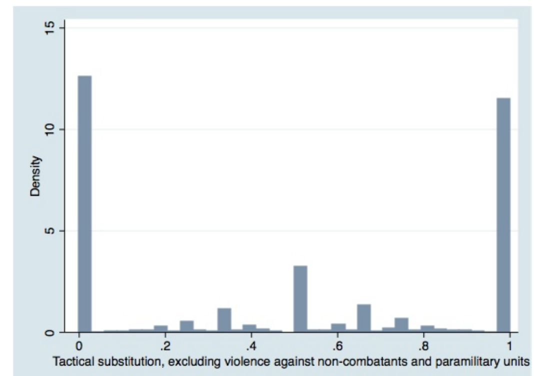
[26] To avoid first and second stage inconsistencies, I invert the classification of $py_{m,t}$ in $X_{m,t}$ such that it takes the value b, where $b \in [0, 1]$ during municipal peace-years. This change is trivial in the linear case and is used to ease estimation of the two-limit Tobit second stage.



(a) Outcome variable, main



(b) Including non-combatants



(c) Excluding paramilitarys

Figure A1: Histograms of main and supplementary measures of tactical substitution, indicating pile-ups at lower and upper limits

B Optimal route equilbria estimation

I solve a classical route optimization problem detailed by Dell (2015) and produce estimates of drug traffic intensity at the municipal level.

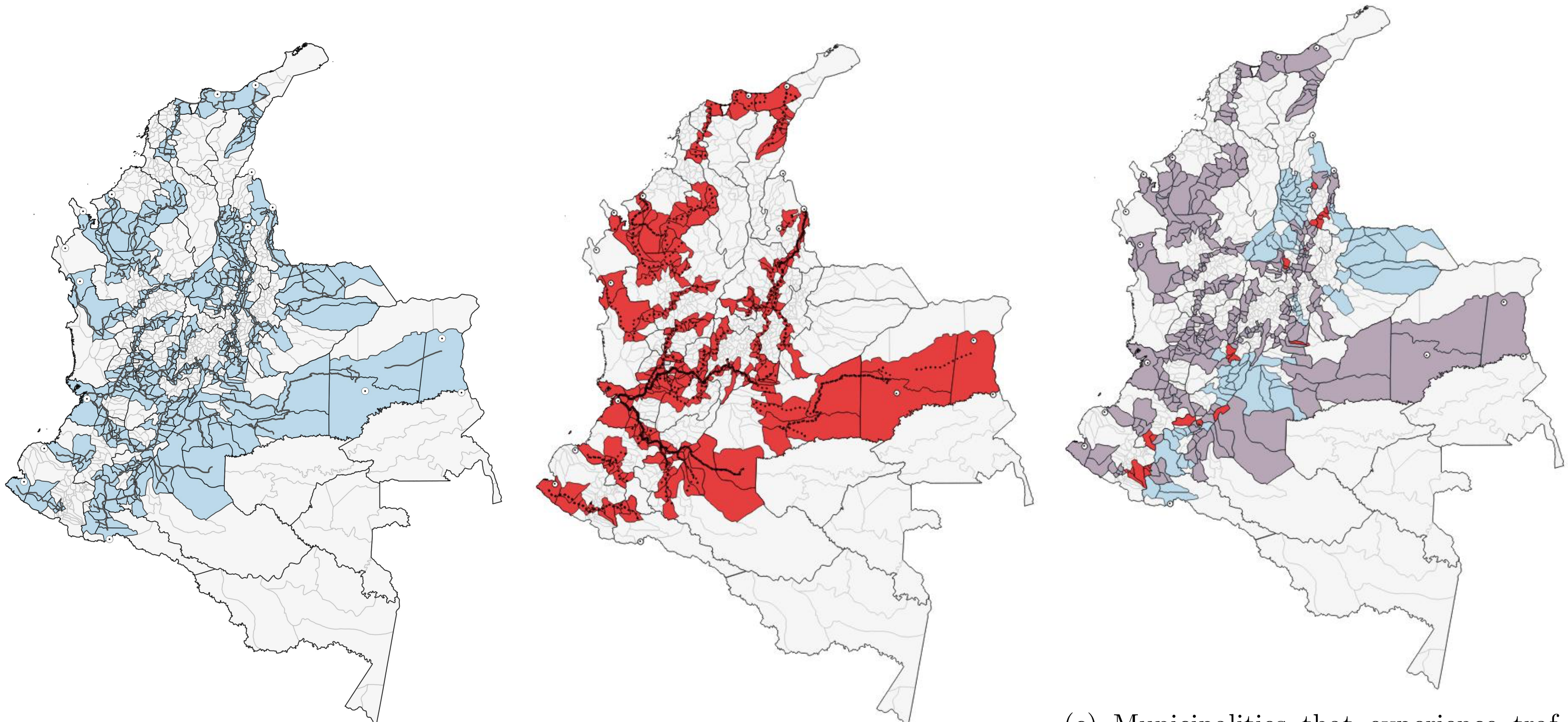
I start with an undirected graph of all major roads in Colombia R composed of intersections N and roadways E (so, $R = (N, E)$). Rebels attempt to move coca paste and cocaine from their strongholds — front bases — to transit points, where drugs exit the country by boat or aircraft. Bases and transit points are drawn from archival data provided by the Colombian Ministry of Defense. Each unit attempts to minimize the cost of shipment. For simplicity, let each roadway $e \in E$ have a cost function determined by the length (l_e) of the road, so the expense of traveling along a given road is equal to $c_e(l_e)$.

Since the purpose of this optimization exercise is study the potential impact of spillovers due to increased drug transit activity, I leave the analysis of congestion dynamics to future research. Drawing on the main findings, one could imagine that such congestion costs might force rebels to reroute traffic following positive shocks to oil production and export (or any other dynamic that increases government capacity), as in figure A2b. In appendix B, I present a map of municipalities that should experience drug traffic *if and only if* increases in government capacity force traffickers to exploit an alternative path around oil producing municipalities (since changes in capacity effectively remove some e from E) (see figure A2c). This might serve as an fruitful extension of the present study.

If traversing $n \in N$ is costless, then the total cost of a potential trafficking route p is $V(p) = \sum_{e \in p} c_e(l_e)$. I assume movement through intersections is costless to avoid imposing additional assumptions on this optimization exercise. Yet counterinsurgents might focus efforts at key junctures in the network. I leave this dynamic to future research.

Let $P_{s,t}$ denote the set of all possible routes between rebel strongholds s and transit points t. Rebels optimize routes such that:

$$\underset{p \in P_{s,t}}{min} V(p). \tag{B.1}$$



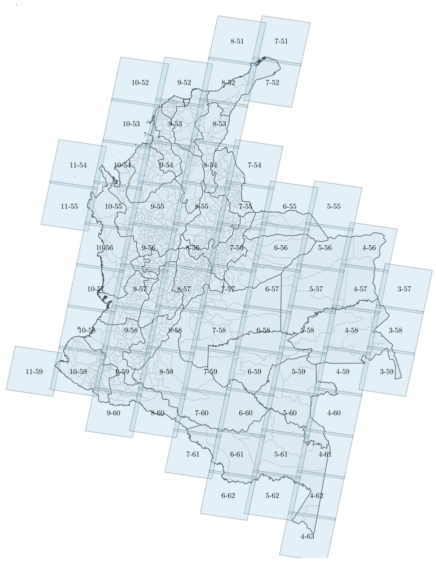
(a) optimal routes without consider potential congestion due to capacity shocks

(b) With congestion due capacity increases via]] positive oil income shocks

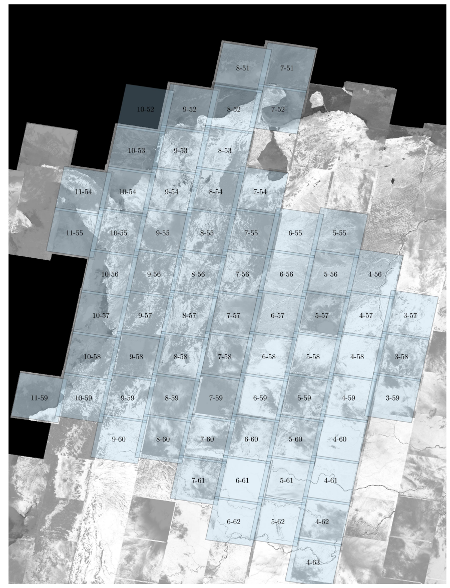
(c) Municipalities that experience trafficking related violence if and only if positive oil income shocks increase congestion costs

Figure A2: Coca trafficking routes, without and with oil shock capacity barriers

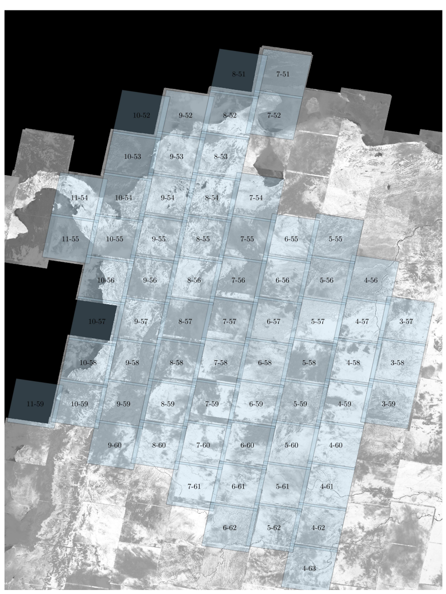
C Geographic figures



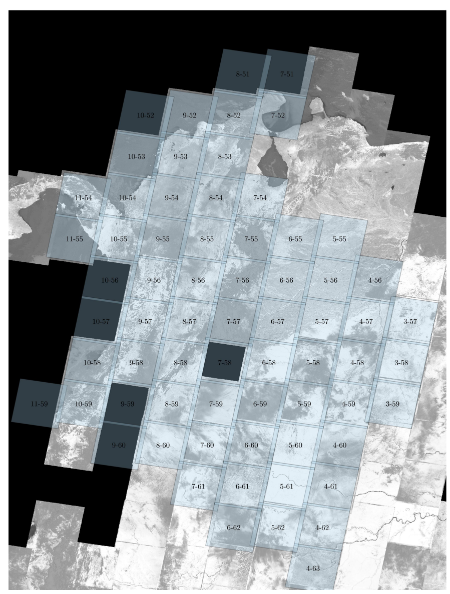
(a) Landsat 5 row/path



(b) 1999 mosaic



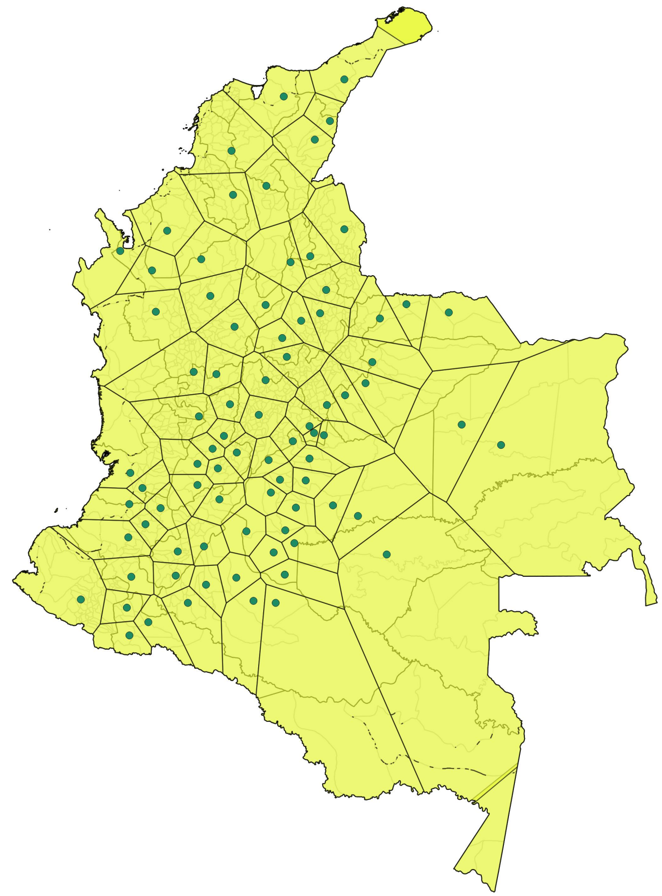
(c) 2000 mosaic



(d) 2001 mosaic

Figure A3: Landsat 5 row/path classification for Colombia and greenest pixel mosaics used for retrospective coca production estimation (1999, 2000, 2001)

(a) Location of counternarcotics airports



(b) Voronoi map of rebel fronts based on confidential historical military data

Figure A4: Counternarcotics airports and rebel base locations

D Additional Tables

Table A1: Overview of first stage inclusion of various instruments in table 1

Instrumental variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Rainfall × price-maker coffee production	✓	✓	✓	✓	✓
Temp. × price-maker coffee production	✓	✓	✓	✓	✓
Rainfall × temp. × price-maker coffee production	✓	✓	✓	✓	✓
Rainfall	✓			✓	✓
Temp.	✓			✓	✓
Rainfall × temp.	✓				✓
Rainfall × soil erosion index		✓			
Rainfall × water accessibility index		✓			
Rainfall × soil suitability index		✓			
Rainfall × Chapare market coca prices			✓		
Rainfall^2 × Chapare market coca prices			✓		
Temp. × Chapare market coca prices			✓		
Temp.^{2} × Chapare market coca prices			✓		
Rainfall^2				✓	
Temp.^{2}				✓	
Atmospheric wind speed				✓	
Atmospheric wind speed^2				✓	
Rainfall × distance to airport					✓
Temp. × distance to airport					✓
Rainfall × temp. × distance to airport					✓

— The first three rows introduce the instruments employed by Dube and Vargas (2013). Coffee sector income is instrumented using the product of cumulative coffee export volume of three major producers (Brazil, Vietnam, and Indonesia) and rainfall variation, price-maker exports interacted with temperature trends and the product of cubic rainfall volume, temperature and major exporter production.

— Rows 4 through 20 introduce novel climatic instruments gathered for this project. I study how rainfall and temperature variation influence the production of coca. In sequential models, I incorporate soil aptitude indices, out-of-country market prices for coca leaves, atmospheric wind speed, and distance to the nearest counternarcotics airport. In the main text, I review potential violations of the exclusion restriction.

Table A2: Weighted regression diagnostics

Panel A: benchmark models with without population weight

	(1)	(2)	(3)	(4)	(5)
Coffee sector shock	0.110**	0.110**	0.0808**	0.0996**	0.113**
	(0.0358)	(0.0351)	(0.0267)	(0.0333)	(0.0370)
Coca sector shock	-0.00260	-0.00238	-0.00309$^{\gamma}$	-0.00303*	-0.00261
	(0.00161)	(0.00162)	(0.00160)	(0.00153)	(0.00162)
Oil sector shock	0.295***	0.293***	0.301***	0.299***	0.295***
	(0.0333)	(0.0353)	(0.0280)	(0.0302)	(0.0326)
Diagnostics					
C-D F statistic	38.90	39.74	35.52	26.51	28.56
Hansen statistic	3.633	1.950	7.012	5.851	5.384
Hansen p-value	0.458	0.745	0.220	0.557	0.613
N	9680	9530	9680	9660	9680

Panel B: benchmark models with average population weight

	(1)	(2)	(3)	(4)	(5)
Coffee sector shock	0.103*	0.105*	0.0674*	0.0835$^{\gamma}$	0.104*
	(0.0504)	(0.0509)	(0.0311)	(0.0441)	(0.0463)
Coca sector shock	-0.00336$^{\gamma}$	-0.00380*	-0.00398*	-0.00327*	-0.00343*
	(0.00172)	(0.00186)	(0.00177)	(0.00167)	(0.00167)
Oil sector shock	0.254***	0.255***	0.260***	0.255***	0.254***
	(0.0418)	(0.0397)	(0.0353)	(0.0406)	(0.0421)
Diagnostics					
C-D F statistic	55.13	54.11	53.14	37.03	39.89
Hansen statistic	4.334	3.247	3.409	7.610	6.823
Hansen p-value	0.363	0.517	0.637	0.368	0.448
N	9680	9530	9680	9660	9680

Dependent variable is $\frac{attacks}{attacks+clashes}$. Municipality fixed effects, year fixed effects, log of population and linear trends by region are omitted. Instruments are noted in the overview of table 1.

- Clustered standard errors in parentheses, department.

$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Additional instrumentation: rainfall and temperature × external production

	(1)	(2)	(3)	(4)	(5)
Coffee sector shock	0.0924*	0.102**	0.0641*	0.0777*	0.0938*
	(0.0426)	(0.0382)	(0.0298)	(0.0338)	(0.0406)
Coca sector shock	-0.00331$^{\gamma}$	-0.00371*	-0.00395*	-0.00298$^{\gamma}$	-0.00333*
	(0.00170)	(0.00166)	(0.00176)	(0.00170)	(0.00163)
Oil sector shock	0.249***	0.248***	0.253***	0.249***	0.248***
	(0.0398)	(0.0388)	(0.0349)	(0.0404)	(0.0403)
Diagnostics					
C-D F statistic	41.28	40.13	39.54	30.73	33.64
Hansen statistic	4.843	4.189	11.61	7.267	8.865
Hansen p-value	0.679	0.758	0.170	0.700	0.545
N	9680	9530	9680	9660	9680

Dependent variable is $\frac{attacks}{attacks+clashes}$. Municipality fixed effects, year fixed effects, log of population and linear trends by region are omitted. Instruments are noted in the overview of table 1.

- Clustered standard errors in parentheses, department.

$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: First stage results of table 1, coffee sector value (coffee sector value regressed on instruments and exogenous regressors)

	(1)	(2)	(3)	(4)	(5)
Oil sector shock	0.0282	0.0369	0.0237	0.0699	0.0196
	(0.0659)	(0.0664)	(0.0622)	(0.0630)	(0.0681)
Rainfall × price-maker coffee production	-0.00353***	-0.00360***	-0.00360***	-0.00353***	-0.00355***
	(0.000933)	(0.000937)	(0.000908)	(0.000905)	(0.000964)
Temp. × price-maker coffee production	-0.215***	-0.221***	-0.287***	-0.216***	-0.216***
	(0.0455)	(0.0453)	(0.0593)	(0.0433)	(0.0461)
Rainfall × temp. × price-maker coffee production	0.000144***	0.000146***	0.000146***	0.000143***	0.000144***
	(0.0000349)	(0.0000350)	(0.0000342)	(0.0000339)	(0.0000360)
Rainfall	-2.491			-0.0721	-4.786
	(1.815)			(0.131)	(7.638)
Temp.	0.00828			0.905	0.100*
	(0.0338)			(1.185)	(0.0421)
Rainfall × temp.	0.00885				0.0162
	(0.00619)				(0.0257)
Rainfall × soil erosion index		0.0331			
		(0.0234)			
Rainfall × water accessibility index		-1.18e-08			
		(3.69e-08)			
Rainfall × soil suitability index		0.0217			
		(0.0367)			
Rainfall × Chapare market coca prices			-0.0351*		
			(0.0148)		
Rainfall^2 × Chapare market coca prices			0.0124*		
			(0.00539)		
Temp. × Chapare market coca prices			-0.00496**		
			(0.00150)		
Temp.^{2} × Chapare market coca prices			0.0000167**		
			(0.00000506)		
Rainfall^2				0.0999	
				(0.128)	
Temp.^{2}				-0.00155	
				(0.00202)	
Atmospheric wind speed				-0.317*	
				(0.145)	
Atmospheric wind speed^2				0.0443*	
				(0.0187)	
Rainfall × distance to airport					0.0241
					(0.0651)
Temp. × distance to airport					-0.000759*
					(0.000283)
Rainfall × temp. × distance to airport					-0.0000791
					(0.000219)
Diagnostics					
AP F statistic	4.528	5.152	5.454	7.393	3.683
AP p-value	0.00325	0.00158	0.000602	0.0000211	0.00399
N	9680	9530	9680	9660	9680

Municipality fixed effects, year fixed effects, log of population and linear trends by region are omitted.
- Clustered standard errors in parentheses, department.
$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: First stage results of table 1, coca sector value (coca sector value regressed on instruments and exogenous regressors)

	(1)	(2)	(3)	(4)	(5)
Oil sector shock	2.596	2.683	2.565	2.683	2.287
	(9.021)	(9.037)	(9.090)	(9.135)	(8.765)
Rainfall × price-maker coffee production	-0.00638	-0.00731	-0.00826	-0.00660	-0.00577
	(0.0105)	(0.0107)	(0.0108)	(0.0106)	(0.0104)
Temp. × price-maker coffee production	-0.188	-0.260	-0.552	-0.223	-0.183
	(0.814)	(0.827)	(0.846)	(0.827)	(0.800)
Rainfall × temp. × price-maker coffee production	0.000582	0.000625	0.000638	0.000595	0.000553
	(0.000560)	(0.000568)	(0.000572)	(0.000565)	(0.000552)
Rainfall	-36.41			2.841	-259.7^{γ}
	(43.59)			(2.520)	(139.9)
Temp.	-0.112			8.262	0.262
	(0.478)			(19.26)	(0.653)
Rainfall × temp.	0.134				0.914^{γ}
	(0.152)				(0.486)
Rainfall × soil erosion index		0.0570			
		(0.647)			
Rainfall × water accessibility index		3.03e-08			
		(0.000000613)			
Rainfall × soil suitability index		0.791			
		(0.895)			
Rainfall × Chapare market coca prices			0.0335		
			(0.221)		
Rainfall^2 × Chapare market coca prices			0.209		
			(0.150)		
Temp. × Chapare market coca prices			-0.0195		
			(0.0189)		
Temp.^2 × Chapare market coca prices			0.0000700		
			(0.0000635)		
Rainfall^2				-0.250	
				(1.505)	
Temp.^2				-0.0145	
				(0.0337)	
Atmospheric wind speed				-0.942	
				(1.436)	
Atmospheric wind speed^2				0.252	
				(0.185)	
Rainfall × distance to airport					1.504^{γ}
					(0.794)
Temp. × distance to airport					-0.00336
					(0.00436)
Rainfall × temp. × distance to airport					-0.00525^{γ}
					(0.00274)
Diagnostics					
AP F statistic	2.957	2.658	2.555	2.657	5.710
AP p-value	0.0270	0.0419	0.0397	0.0247	0.000171
N	9680	9530	9680	9660	9680

Municipality fixed effects, year fixed effects, log of population and linear trends by region are omitted.
- Clustered standard errors in parentheses, department.
$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: Reduced form of table 1 (tactical substitution regressed on instruments and exogenous regressors)

	(1)	(2)	(3)	(4)	(5)
Rainfall × price-maker coffee production	-0.000372*	-0.000375**	-0.000349*	-0.000373**	-0.000375**
	(0.000145)	(0.000145)	(0.000140)	(0.000142)	(0.000143)
Temp. × price-maker coffee production	-0.0234***	-0.0257***	-0.0219**	-0.0232**	-0.0235***
	(0.00657)	(0.00653)	(0.00735)	(0.00714)	(0.00652)
Rainfall × temp. × price-maker coffee production	0.0000145*	0.0000148*	0.0000139*	0.0000147*	0.0000146*
	(0.00000588)	(0.00000590)	(0.00000560)	(0.00000572)	(0.00000583)
Rainfall	-1.178			-0.0444	-0.322
	(1.235)			(0.0661)	(3.445)
Temp.	-0.0162$^{\gamma}$			0.312	-0.00695
	(0.00860)			(0.352)	(0.0154)
Rainfall × temp.	0.00391				0.000892
	(0.00427)				(0.0118)
Rainfall × soil erosion index		0.0176			
		(0.0143)			
Rainfall × water accessibility index		2.82e-09			
		(2.13e-08)			
Rainfall × soil suitability index		-0.0321			
		(0.0229)			
Rainfall × Chapare market coca prices			-0.00213		
			(0.00439)		
Rainfall^2 × Chapare market coca prices			-0.00187		
			(0.00390)		
Temp. × Chapare market coca prices			0.000154		
			(0.000266)		
Temp.^{2} × Chapare market coca prices			-0.000000522		
			(0.000000899)		
Rainfall^2				0.00652	
				(0.0565)	
Temp.^{2}				-0.000566	
				(0.000611)	
Atmospheric wind speed				0.0669*	
				(0.0302)	
Atmospheric wind speed^2				-0.00144	
				(0.00408)	
Rainfall × distance to airport					-0.00541
					(0.0272)
Temp. × distance to airport					-0.0000767
					(0.000105)
Rainfall × temp. × distance to airport					0.0000191
					(0.0000918)
N	9680	9530	9680	9660	9680

Dependent variable for all models is $\frac{attacks}{attacks+clashes}$. Omitted exogenous regressors include a population measure and oil sector shocks. Municipality fixed effects, year fixed effects, log of population and linear trends by region are also omitted.
- Clustered standard errors in parentheses, department.
$^{\gamma}$ $p < .1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$