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Commodity Booms, Conflict, and Organized Crime The Economics of Oil Palm Mafia Violence in Indonesia

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Abstract: This paper examines the relationships between agrarian commodity booms and the incidence of group conflict and criminality in the context of Indonesia's expanding oil palm sector. It theorizes that commodity boom violence takes two main forms: low level but organized criminal violence involved in the extortion of "rents" produced by a given commodity extraction and production process (extortion); and violent competition among a range of groups, including "mafias", youth gangs, landholders, and commercial producers for control of these rents (competition). Extortion and competition violence are associated with distinct temporal distributions consistent with our theory. Criminality–especially theft–is higher in villages with established and productive oil palm plantations (extortion), whereas villages undergoing planation expansion have a higher incidence of group conflict (competition). A dynamic analysis utilizing panel data at the sub-district level support our causal interpretation, as the relationship between the area under oil palm cultivation and resource conflict (competition) changes over time and with prevailing commodity prices. Our results are robust to the use of instrumental variable analysis to account for the potential endogeneity of plantation expansion. Our theorized mechanism is given further support by a targeted primary survey of nearly 1,920 respondents in oil palm producing and non-producing villages, which shows that villages experience different rates of extortion and competition violence depending both on if, and when, oil palm production commenced.

Key words: Oil palm; mafia; natural resources; political economy; violence; organized crime

JEL Codes: D74, L73, O13, Q33, Q34

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1 Introduction

Commodity booms – large-scale increases in the demand for and production of raw materials or primary agricultural products – are frequent occurrences (Carter et al., 2011). The second half of the nineteenth century saw booms in demand for citrus and sulfur from Italy, guano from Peru, and beef from Argentina. The advent of the next century brought about a surge in rubber cultivation in Brazil, Malaya, and the Dutch East Indies. The 2000s produced booms across a wide range of raw materials and agricultural products, from cobalt and zinc in the Congo to wheat and wool in Australia. Both intuition and annecdotal evidence suggest that such booms is likely to have distruptive social consequences. Yet much theoretical and empirical research is ambiguous on the impact of commodity booms on specific outcomes such as conflict and crime. On the one hand, such booms can increase incomes and hence depress crime and conflict; on the other, surges in wealth and inequality increase both the incentive and opportunity for rapacity Nillesen and Bulte (2014). To address this ambiguity, empirical researchers have picked up on the distinction between "diffuse" and "point" resources made by Auty et al. (2001). According to this approach, the more concentrated the resource (point rather than diffuse), the more likely *any* violence is to result. Recent scholarship has thus tended to draw a distinction between more dispersed agricultural production, which should decrease violence, on the one hand, and more concentrated raw material extraction, which should increase it, on the other. Finding this approach too crude, this paper proposes and tests a more refined theoretical account of the effect of commodity shocks on the incidence of different types of violence in agricultural commodity producing locales.

The prevailing approach to modeling the effect of commodity production on violence and crime follows the logic of Becker (1968). In this sense, agricultural commodity booms may be expected to reduce the level of criminality and conflict because the "opportunity cost" of predation vis-à-vis farming for individuals is elevated during periods of high farm gate prices. In contrast, surges in demand for high value-to-mass commodities, such as precious metals and minerals, provide greater temptations for individuals to engage in rapacious behavior, both because the economic gains of the boom tend to be more unequally distributed (i.e., favoring resource owners rather than workers) and physically concentrated (e.g., a gold mine), and because the rewards to theft are relatively greater (Draca et al., 2018; Humphreys, 2005; Sidebottom, 2013). Some empirical research on larger-scale conflicts provides suggestive support for just such a conditional effect, with increases in agrarian commodity prices associated with a decrease in the risk of civil war, but increases in raw material prices associated with an increased risk of such conflict (Dube and Vargas, 2013; Berman et al., 2017; Ciccone, 2018; Collier, 2000). However, not all research is in agreement on this point (Angrist and Kugler, 2008; Bazzi and Blattman, 2014; Brückner and Ciccone, 2010; Milląn-Quijano, forthcoming; Fearon, 2005; Sánchez de la Sierra, 2020), most likely because the conventional equation of raw materials with point resources and primary agricultural products with diffuse resources is too coarse (Auty et al., 2001). This paper argues that it is necessary to consider how the specific production technology of a given commodity yields opportunities and incentives for organized extortion.

To develop and test our argument, we examine subnational variation in conflict and violent crime rates in Indonesia in the years either side of the mid-2000s commodity boom. Focusing on a surge in demand for a single product category – oil palm – we analyse the implications that its specific production technology has, not only for the distribution of the economic gains of the boom, but also for the opportunities for theft and extortion that a price shock and associated expansion in production generate. Fueled by a surge in global demand, Indonesia rapidly expanded oil palm production from about 15 million tons in 2005 to 31 million tons in 2015.[1] We find evidence that oil palm is the highest income-earning crop among smallholder agribusinesses (Rist et al., 2010; Euler et al., 2016, 2017). Thus, on one level, we might expect the oil palm boom to be associated with a drop in violent crime as the opportunity cost of criminality vis-à-vis farming increases. However, we instead theorize that even as incomes for smallholders increase, the technology of oil palm production yields opposing incentives for non-producing groups with the capacity for organized violence. Oil palm has characteristics of both point and diffuse resources. That is, even though cultivation is widely dispersed, the intensive nature of oil palm production and its long supply chain mean that its expansion gives rise to multiple opportunities for illicit gain by lightly armed rural gangs that we follow locals in calling "oil palm mafias" (*mafia sawit*). These so-called mafias specialize in theft, extortion, and market manipulation in areas of agricultural commodity cultuvation, processing, and distribution. In turn, these low level criminal organizations compete violently with each other and with other actors in the oil palm supply chain for control of these rents.

To investigate the mechanisms linking oil palm expansion to violent crime and conflict, we conducted several months of original fieldwork in six randomly selected oil palm producing villages in two districts in the province of South Sumatra, the region where the majority of recent palm oil plantation expansion has occurred. The two fieldwork districts, Ogan Komering Ilir and Musi Rawas Utara, were first randomly selected from those districts which had extensive oil palm plantation coverage and which had experienced violence in the recent past. Cases were thus selected to be illustrative rather than representative (Seawright and Gerring, 2008). Drawing on this fieldwork, we theorize that violence is likely to be of two main types. The first is the low-level but sustained criminal violence involved in the extortion of rents produced by a given commodity extraction and production process. The forms of predation we document, including the theft of oil palm fruits from plantation owners, extortion and intimidation of farmers, participation in land

[1] Although the 2000s commodity boom was broad-based, with other Indonesian cash crops such as rubber also seeing a surge in prices, other commodities did not experience as rapid an expansion.

disputes, and generalized criminality is primarily in the purview of armed gangs, or indeed, mafias; we call this low-level but neverthless organized criminal activity *extortion* violence. The second type is violent competition among various actors for control of the industry's rents; we term this *competition* violence. The actors engaged in this type of violence include not only mafia organizations, but also youth gangs, local ethnic associations, and plantation companies and their armed agents and allies. These two types of violence should be associated with distinct temporal distributions. *Extortion* violence should be relatively constant over time, albeit confined to established or productive locales where rents can be extracted. *Competition* violence, in contrast, should be elevated during moments of expansion, when no group has come to establish a local monopoly over rent extraction, and during moments when either the cost of contesting control is lowered (e.g., a glut of weaponry) or the potential gains from victorious contesting an existing monopoly are elevated (e.g., a price shock).

To quantitatively estimate the relationships between the boom in oil palm production and conflict and crime, we adopt several empirical strategies. First, we utilize panel data on oil palm coverage from 1995 to 2015 derived from satellite imagery, which allows us to calculate the intensity of oil palm cultivation in a location (village [*desa*] or sub-district [*kecamatan*]). This data is available for the main oil palm producing regions: Sumatra, Kalimantan, and Papua. We combine this with violent crime data (*extortion*) and mass violence and conflict data (*competition*) from the Village Potential Survey (PODES) 2014 for a cross-sectional analysis and from the National Violence Monitoring System (NVMS) from 2005 to 2014 to study trends in patterns of both types of violence. Our unit of analysis is the village for the cross-sectional study and the sub-district for the dynamic analysis. We classify each location into three groups–non-producing areas (i.e, those without oil palm production by 2015); post-boom producing areas (i.e., those that began planting after 2005 but not before), and old oil palm producers (those that had begun before 2005), and econometrically compare the incidence and trajectory of violence and conflict across these groups. Second, to address any potential bias in the aggregate indirect sources of violence data (PODES and NVMS), and to further probe the hypothesized mechansisms and temporal dynamics, we analyze the data from a primary survey of 1,920 respondents in oil palm producing and non-producing villages in the provinces of North and South Sumatra.

The cross-sectional analysis shows that *Extortion* and *competition* violence are associated with distinct temporal distributions consistent with our theory. Criminality–especially theft–(*extortion*) in 2014 is higher in villages with established and productive oil palm plantations (pre-2005), whereas villages undergoing planation expansion (post-2005) have a higher incidence of group conflict (*competition*). The dynamic analysis utilizing panel data at the sub-district level also support our causal interpretation, as the relationship between the area under oil palm production and conflict changes over time. The level of criminality in a sub-district is also strongly increased by having a greater share of its area under oil palm production. However, the impact of oil palm production on the incidence of resource conflict (*competition*) is stronger when international prices for oil palm are high; resource conflicts escalate after 2008, peak in 2012, and gradually decline thereafter. Our quantitative results are robust to the potential endogeneity of oil palm production, which we address by utilizing information on agro-climatic suitability of the location to oil palm cultivation. Finally, using data on individual perceptions and personal experiences, the survey results also confirm that villages experience different rates of *extortion* and (*competition* violence depending both on if, and when, oil palm production commenced.

This paper contributes to four related sets of research. First, this paper adds both empirically and theoretically to research on the economics of crime (Freeman, 1999). In their recent review of the literature, Draca and Machin (2015) note that early research found weak and inconsistent effects of economic shocks on crime, not least because the effect is likely to be confounded by reverse causality and omitted variable bias. The turn towards more precise causal identification in recent empirical studies has yielded more robust results. Largely supporting Becker's classic hypothesis (Becker, 1968), Dix-Carneiro et al. (2018) and Dell et al. (2019) utlize trade shocks to demonstrate that negative labor market conditions, especially for young men, are positively associated with the incidence of violent crime in Brazil and Mexico respectively. In this paper, in contrast, even though incomes are *higher* among smallholder oil palm farmers, the incidence of violent crime is nevertheless elevated in areas with established oil palm plantations. Focusing on the presence of locally lootable agricultural commodities, our paper is closer in spirit to that of Dimico et al. (2017), who demonstrate that the Italian Cosa Nostra had its origins in the lemon growing regions of Western Siciliy during the nineteenth century boom in demand for citrus (as a then recently discovered prophylactic for scurvy). In that case also, choke points in harvesting and processing made extortion and theft by armed gangs or "mafias" possible, while the diffuse nature of cultivation and absentee ownership made regular policing more difficult. We thus theorize that the specific production technologies associated with an economic shock are an important consideration in determining the latter's relationship with violent crime. Not all commodity sectoral shocks are created equal.

Second, this paper also contributes to debates on the microdynamics of conflict associated with the primary commodity sector. Research on the relationship between commodity booms and large scale violence is substantial (Nillesen and Bulte, 2014; Ross, 2015). A large body of research has shown that increased prices for capital intensive mineral commodities is associated with higher violence as groups compete for control of the sector's profits (Ross, 2015; Dal Bó and Dal Bó, 2011; Bellows and Miguel, 2009; Weinstein, 2006). However, research on agrarian commodities has yielded more mixed results, as our theoretical model would anticipate. Some resesarch tends to support the "opportunity cost" hypothesis, with elevated commodity prices being associated with lower levels of conflict (Dube and Vargas, 2013; Berman et al., 2017; Bazzi and Blattman, 2014; Brückner and Ciccone, 2010; McGuirk and Burke, 2017; Ciccone, 2018; Markowitz, 2017; McGuirk and Burke, 2017; Humphreys, 2005; Thies, 2010). Other research, however, yields exactly the opposite results (Angrist and Kugler, 2008; Brückner and Ciccone, 2010; Millạn-Quijano, forthcoming) or no relationship at all (Fearon, 2005). We argue that the particular characteristics of a given commodity matter. We show that like other lootable natural resources, but unlike many bulk commodities, oil palm production is associated with multiple choke points in the process of production that both facilitate extortion and foster rivalies for control over these illicit incomes (Dube and Vargas, 2013; Berman et al., 2017; Bazzi and Blattman, 2014; McGuirk and Burke, 2017; Ciccone, 2018).

Third, our findings resemble those on the effect of competition between armed groups for control over choke points in the production and transport of illegal commodities, especially narcotics. In South and Central America, the Sahel, and elsewhere violence has been shown to be responsive to levels of competition between rival mafias or gangs for control of the trade, especially in the context of demand and supply shocks (Angrist and Kugler, 2008; Castillo et al., 2018; Durán-Martínez, 2015; Magaloni et al., 2019; Metelits, 2009; Millạn-Quijano, forthcoming; Strazzari, 2015; Yashar, 2018). Our results indicate, however, that mafia or gang violence does not depend on the illegality of the sector, or on the absence of the state as an enforcer of property rights (Andreas and Wallman, 2009; Cockayne, 2016; Snyder and Duran-Martinez, 2009). We find evidence that the rapacity mechanism previously only associated with high value goods such as mineral oil or illicit commodities such as cocaine, may also be present in at least some legal agricultural commodity sectors, where there are potentially positive returns to racketeering and other forms of violent crime (Catino, 2019; Critchley, 2008; Gambetta and Reuter, 1995; Raab, 2016; Reuter, 1987; Ross, 2001).

Last, this case allows us to distinguish between the effects on violence and crime associated with the production of a commodity and of its expansion per se (Ross, 2001). We find evidence for both types of association. Utilizing subnational variation in the timing of plantation expansion and commodity price variation, we show that extortion of the rents associated with commodity production are more salient in explaining violent crime, especially theft. We find that the association between violent crime and oil palm cultivation is evident only after palms have become productive (i.e., between five and ten years after planting). This supports the argument that much of the violence is the result of extortion and theft of individuals in closest proximity to areas of established oil palm production. However, we find evidence that larger scale conflict is more common during the expansion phase, as rival groups contest control over existing and future rents produced by the sector. This finding is consistent with evidence on the violence produced by inter-mafia competition, where variation both in the size of the rent pool and in the barriers to entry over time and space determine the frequency and severity of group violence (Cockayne, 2016; Dell, 2015). Temporal dynamics, in short, should be a core consideration of research into the political and social effects of commodity shocks.

2 Background: Oil palm expansion in Indonesia

Oil palm (*elaeis guineensis*) is an edible tropical oil, which grows only within a narrow band of ten degrees north and south of the equator. Demand for it has grown exponentially over the last two decades. Its ubiquity in global consumer goods manufacturing is hard to overstate; oil palm contributes to about half of the packaged products sold in grocery stores in the United States. Imports to the United States alone rose from less than 200,000 metric tons in 2000 to 1.6 million metric tons in 2019. Prior to the COVID-19 outbreak, global production was predicted to hit 84 million tons in 2020. The commodity price boom of the late 2000s and early 2010s provided a strong economic incentive for oil palm expansion (see Figure A1 in the Appendix, which depicts the rapid rise in prices for processed palm oil). The spikes in prices were caused in large part by a sharp rise in demand from fast growing developing economies, especially China and India. Global oil palm production is concentrated overwhelmingly in Southeast Asia, with Indonesia having recently taken over Malaysia as the world's biggest exporter. About three-fourths of the Indonesian oil palm crop is exported (see Figure A2a in the Appendix), accounting for just under 10 percent of the nation's total export earnings. The industry employs 5.9 million people directly, with up to 50 million more jobs depending indirectly on the sector.[2]

Indonesian production and exporting of palm oil increased rapidly in the mid-2000s. The expansion of the area under oil palm cultivation far outpaced any other estate crops (see Figure A2b in the Appendix). The period from 2000-2005 saw modest growth of just 0.6 million hectares, as the post-democratic transition central government lost its "fiscal, administrative, and coercive" capacity to expand plantations (McCarthy and Cramb, 2009). However, a rapid acceleration in planation expansion took place during the post-2005 boom in commodity prices. Palm area increased from 3.6 million hectares in 2005 to 5.2 million hectares in 2010 and to 6.7 million hectares in 2015. The expansion of oil palm plantation coverage has been concentrated in particular provinces (see Figure A3). Riau, North Sumatra, and West and Central Kalimantan are the largest palm producing provinces in terms of planted area, each with over 1 million hectares in 2015 (see Table A1). In 2016, 60 percent of Indonesian production area was located in provinces in Sumatra, whereas 35 percent was located in Kalimantan. Recent expansion has been heavily biased towards large-scale planations. Data from Badan Pusat Statistik (BPS) – the Indoensian Statistics Bureau – show that the number of large

[2] https://www.globeasia.com/special-reports/palm-oil-matters-indonesia/

plantation companies increased from 693 in 2000 to 1,600 in 2015 (Badan Pusat Statistic, n.d.). In the same period, the area of large plantations increased from under 3 million hectares to 6.7 million hectares, while those of smallholders remained constant at 3.5 million hectares.

There are multiple physical and temporal points in the oil palm production supply chain (Danzer, 2008, 27). Oil palm plantation cultivation is extensive, taking up vast tracts of territory. It is also largely monocropped, unlike some other cash crops, such as rubber, which as defoliatimg species can be co-planted with pineapple or other crops. Thus, oil palm plantations generally "expand to take up all space" (Li, 2017a, 5) in a given area, pushing out all other forms of agrarian production. In Indonesia, such plantations have rolled out over pre-existing hamlets, farms and forests, with villages often enclaved within vast expanses of oil palm trees. Oil palm plantations when viewed from the air are striking in their scale and monotoneity. For large parts of the year, plantations can be "eerily empty of people" (Li, 2017a, 3), with a productive oil palm plantation needing only one worker for every 8-10 hectares compared to one worker for every 2 hectares for rubber cultivation (Li, 2016, 354).

At other times of the year, however, activity on plantations can be intense. Oil palm production requires the highly coordinated operation of mobile work gangs to harvest the fresh fruit bunches (FFB), transport them by truck to processing mills, and to spread fertiliser and pesticide through the plots. Because FFBs are heavy and need to be taken for processing within 48 hours of being harvested, oil palm production and harvesting is relatively capital intensive (McCarthy and Cramb, 2009). Moreover, because Southeast Asia has a single monsoon, it has only one peak-harvesting season, in contrast to Central and West Africa, which have two. The oil winning process involves the reception of FFBs from the plantations, sterilizing and threshing of the bunches to free the palm fruit, mashing the fruit, and pressing out the crude palm oil. The crude oil is further treated to purify and dry it for storage and export. Even a medium-scale operation thus demands a sustantial processing and transport infrastructure, with processing concentrated into a small number of local facilities.

3 Theoretical Argument

In the context of a commodity boom, small-scale theft and extortion by indivdiuals criminals is of course possible. However, the theft of bulky commodities such as oil palm fruit on an economically efficient scale, the extortion of commodity transporters at road blocks, or the maintenance of a protection racket for commodity processors are all beyond the capability of individual criminals. Moreover, small-holder farmers may themselves be lightly armed, while larger plantations and processors can afford to employ private security guards or engage the police or army for protection, increasing the risk of theft to individual criminals. This means that commodity boom violence is primarily an *organized criminal activity.* Our fieldwork revealed that the main driving force behind interpersonal and group violence was activity associated with what local people call the "oil palm mafia". The term "mafia" is used frequently in Indonesia to refer to networks made up of corrupt officials, security officers, traders and criminal gangs that specialize in extortion, theft, and manipulation in the markets for specific agricultural commodities, with coffee, rice, shallot, sugar, tobacco, and maize "mafias" being among the other examples.[3] In some cases these mafias or gangs (*preman*) cohere along ethnic cleavages, but this feature appears to be incidental rather than central to their function. Assuming that gangs or mafias operate as rational, profit maximizing agents, we theorize that violence in the commodity sector will be of two types, which we term *extortion* and *competition* violence.

3.1 Extortion

All agricultural commodities, beyond the quantity produced for subsistence, generate rents (Murphy et al., 1993). These rents can be captured by primary producers, transporters, processors, the state, or indeed, any actor with the ability to use legal or illegal means to monopolize the economic surplus generated at various points along the supply chain. Agrarian commodity booms can have diverse effects on the likelihood of violence depending on their associated production technologies, which in turn affects the level and distribution of rents. The scale of production and the types of transportation and processing required should impact incentives for organized violent criminal activity, namely the *extortion* of producers, transporters, and processors. The more that the production of a particular agricultural commodity is dominated by large-scale plantations, and the greater degree to which there are choke points in the transport and processesing stages of the production chain, the greater are the potential gains from theft and extortion (Gambetta and Reuter, 1995; Reuter, 1987).

Although violence may be much more likely in illicit sectors of the economy (e.g., narcotics), where the state does not provide an armed backstop for the enforcement of private property rights (Andreas and Wallman, 2009; Yashar, 2018; Snyder and Duran-Martinez, 2009), expansive legal planations are almost impossible to continuously monitor, and are characterized by de facto low state presence, generating oppor-

[3]In sociological terms, a "mafia" refers to a specific type of criminal organization "which produces, promotes, and sells private protection" (Gambetta, 1996, 1). Strictly speaking, some of the entities in the Indonesian context might be better described as "violent entrepreneurs" who use violence or the threat of violence to gain an advantage in a market, including through theft or extortion (Volkov, 2016). However, to the extent that these groups are successful in establishing a local monopoly of extortion on commodity production in a given territory, they often use their capacity as specialists in violence to also engage in more prototypical "mafia" activity, i.e., protection. Indeed, although some other food mafias predominantly engage in gouging domestic consumers, the oil palm mafia, which encapsulates a large number of independent, sometimes cooperating and sometimes clashing gangs, instead focuses primarily on extorting sellers and middlemen in the sector, and secondarily on associated criminal activities in palm producing locales, especially the selling of protection services to oil palm transporters, processors, and others who use road networks in their territory. It is in this latter sense that the term "mafia" seeems particularly warrented in the case of oil palm criminality (Gambetta, 1996).

tunities for both theft and protection services. Additionally, an oligopolistic market for either commodity transport or processing or both, creates further avenues for extortion (Critchley, 2008; Raab, 2016). Given what we know about the concentration of rents in the oil palm production process, our primary hypothesis is that oil palm cultivation, especially on larger plantations, should be associated with an increase in the incidence of theft and violent crime. A further expectation is that *extortion* violence should occur largely after oil palms have become productive, not before. Oil palm takes approximately four years after planting to begin generating fruits, with peak productivity occuring at about ten years. This implies that we should begin to see *extortion* violence approximately five years after palms have been first planted rather than during the land acquisition, forest clearance, or initial planting stages themselves.

These hypotheses of routinized theft and extortion in oil palm producing locales find support in our fieldwork. While some theft takes place in day time in the open (e.g., stealing harvested FFBs awaiting collection on roadsides), there is also a more organized version in which gangs using trucks raid company estates at nights, rapidly and carelessly harvest FFBs, and sell them to middlemen who then transport them to processing factories (often located in rival plantations from where the theft occurred). A related form of violence is more generalized criminality in the communities and roads surrounding the plantations themselves. Villages in oil palm producing districts are marked by high levels of violent predatory crime, including robbery and hold-ups on highways and plantation roads, as well as kidnapping for ransom. In one case, village youths ran a protection racket on the main road, in which they would provide "security" for oil palm and other goods trucks – requiring them to display stickers produced by the group, and sometimes riding shotgun with drivers accompanying them along the road. In other cases, such as at government weigh stations, protection rackets were conducted in collaboration with police and other state officials.

3.2 Competition

A second mechanism linking oil palm plantation expansion and violence is conflict among rival actors for control of choke points in production, transport, and processing activities associated with the industry (i.e., *competition* violence). As Yashar (2018) has shown, competition between criminal organizations for control of the economic surpluses in the narcotics transport sector are associated with higher levels of violence. Although Yashar (2018) marshalls persuasive evidence to document the link between competition and violence, the level of competition is exogenously given in this account. Other research shows how changes in supply and demand for the commodity (Angrist and Kugler, 2008; Castillo et al., 2018; Durán-Martínez, 2015; Magaloni et al., 2019; Metelits, 2009; Millan-Quijano, forthcoming; Strazzari, 2015) and changes in barriers to entry (Dell,

2015) affect the frequency and intensity of violent group competition. What specific conditions are likely to increase competition among gangs in the oil palm sector?

First, we anticipate a temporal effect. The logic is analogous to that of inter-firm competition in a legal market. When a new market is created (e.g., through the deregulation or privatization of an existing sector or the emergence of a new technology), we would expect to observe multiple firms competing for market share, with the number driven largely by the relative costs of entry and size of the market. For example, in the early years after the discovery of oil in East Texas at the start of the twentieth century, the sector was highly fragmented among multiple small-scale operators. This logic also applies to illicit markets. With the introduction of prohibition in the United States in the 1920s, multiple new criminal organizations emerged to challenge incumbent gangs for control of the lucrative new illegal trade (Cockayne, 2016, 114-18). We were unable to observe this expansion phase in our own fieldwork, but in both of our case-study districts, local land-rights advocates have compiled many reports of legal disputes, protests and occupations, as well as violent clashes between local landowners and plantation companies. To cite one of the most deadly such clashes, a long-running land conflict in the village of Sungai Sodong (not far from our case-study villages in Ogan Komering Ilir), culminated in tit-for-tat violent clashes in April 2011: private security guards linked to the plantation company first attacked villagers, killing two, prompting a reprisal attack in which villagers raided the company mess and killed five company workers they encountered there. There is moreover an extensive qualitative literature on land-grabbing and land conflict in Indonesia and beyond, which documents the often violent confrontations that can occur when local landowners resist attempts by companies to establish oil palm and other plantations (Hall, 2011; Li, 2017a,b; Levang et al., 2016; Lund, 2018). Plantation companies themselves often operate in ways that violate formal laws or take advantage of legal "gray zones" (McCarthy, 2004) (such as overlapping land tenure and competing authority), and they frequently use state security forces (to whom they provide private payments), security firms, local gangs and other militias and paramilitaries to enforce their dubious legal claims. Plantation and other natural resource companies themselves, in effect, often operate in ways that are akin to gangs, relying on extra-legal coercion to establish control of resource production, a phenomenon found in many natural-resource industries (compare with the extensive literature on oil companies and private armies in West Africa, see for example: Von Kemedi (2003)).

To the degree that there there are returns to scale (i.e., high fixed costs and low marginal costs), however, we would expect the number of competitors to fall over time. This, of course, is what happened to petroleum oil extraction in Texas. Some sectors, indeed, particularly lend themselves to monopolization, with a single firm controlling all of the rents produced in that sector. In the case of the American mafia, by the early 1930s, just five families had come to dominate the criminal underworld with a consequent reduction in intra-group violence (Cockayne, 2016, 120). Thus, in our case, we posit that conflict is likely to be elevated first during an expansion phase, when production first comes online, but during which no single producing or intermediary group yet controls production and trade. In our fieldwork sites, we found that violence stemming directly from conflict over land tended to occur mostly during, or shortly after, the expansion phase. Of our six case-study villages, only one, Padang Pasir, had experienced this form of violence within the last 15 years and the violence recorded referred primarily to property damage. Other evidence from the primary commodity sector in Southeast Asia suggests that competition between a range of actors including plantation companies, armed gangs, indigenous groups, and even the military is especially intense during the early phases of land acquisition and clearance (Ross, 2001; Li, 2017a). In contrast, although criminal violence *extortion* should remain high during the maturity phase, conflict between armed groups should be lower as a local monopoly has been established and rents are stable.

Economies of scale and high entry barriers mean that, all else equal, conflict as a result of competition should deteriorate as a palm plantation matures. Indeed, in our fieldwork, we find that in mature plantation areas, rival gangs divide plantations into distinct blocks so as not to compete directly for fruits, and thieves typically make payments to company security, police and military officers. Companies, too, have generally come to stable arrangements with security forces, gangs, and local communities. Although the operations of the mafia occasionally result in violent clashes and arrests when thieves encounter rival groups or company security on plantation roads, these de facto agreements reduce the incidence of major violent episodes. However, gangs, like firms, should respond to changing market prices. We posit that gang entry into the market should be higher where prices and rents increase (Hopenhayn, 1992). Previous research on larger scale organized violence–civil wars–has found that increases in the price of labor-intensive agricultural commodities may decrease conflict as workers prefer increased wages to the risk of predation–an *income* effect–while an increase in the price of capital-intenstive commodites such as oil may increase armed conflict as state and non-state entities compete to control the sector's higher rents–a *rapacity* effect (Dube and Vargas, 2013; Berman et al., 2017; Bazzi and Blattman, 2014). However, owing to the unusual characteristics of oil palm production that we described in the background section, in many respects it is closer to a capital-intensive point resource than to a diffuse agrigultural one (Auty et al., 2001). Although farm gate prices may vary to a degree with international market fluctuations, the income effect is likely to be small, with little impact on the opportunity cost of predation for individual farmers or laborers. The biggest price shock is likely to be felt at the intermediary levels of transit and processing, where profits and rents are concentrated. If the pool of rents increases sufficiently due to higher prices, the potential prize for those willing to violently contest control over the rents associated with the transportation and processing of oil palm excedes its costs.

We thus anticipate a price threshold across which violent competition among gangs, and between gangs and others in the production chain (e.g., plantation companies, native landholders), should intensify. Again this hypothesis finds tentative support in our fieldwork. Although we were not able to directly observe long-term patterns of violence through our qualitative fieldwork – which occurred at one point rather than over an extended period of rising and falling production – it is notable that many of the large-scale instances of violence recounted by informants occurred during the post-2005 boom. Echoing our logic, local informants explained that higher commodity periods tended to reawaken old resentments among dispossessed land owners, leading to renewed land claims and, especially, increased confrontations and extortion between neighbouring smallholder and dispossessed/mafia villages.

4 Empirical analysis

We next quantitatively examine the relationship between oil palm production and manifestations of extortion and competition violence, using data on empirical analogues to these concepts. Extortion violence may manifest itself as crimes such as theft and robbery, where as competition violence appears as group conflicts (large scale violence involving multiple people, conflict over land and resources, etc.). Such information has been systematically collected for Indonesia by the National Violence Monitoring System (NVMS) and tri-annual Village Potential Survey (PODES). We also collect new data on individual experience of violent crime through a primary survey. The goal of our analyses is to determine whether indicators of extortion and competition violence vary systematically with prevalence and expansion of oil palm plantation production.

4.1 Econometric strategy

We estimate a linear relationship between oil palm production and extortion and competition violence. We hypothesize that additional intensity in oil palm production is associated with greater incidence of theft, robbery, large scale violence, resource conflict, and other measures of violence. We also anticipate different types of violence to exhibit at different stages of oil palm development. Our data allows us to categorize a location into three types based on how recently it engaged in oil palm production: (1) No oil palm production by 2015 (*no palm*); (2) Palm production in 2005 but not earlier (*post-boom*); and (3) Palm production since 1995 (possibly earlier) (*pre-boom*). By analyzing the trajectory of violence in these different types of locations, we can determine the dynamic relationship between oil palm expansion and violence. Given that the timing of production matters for generating violent crime, we should find statistically significant differences in patterns of violence across the various types of locations.

In devising our empirical strategy, we consider the possible problems with using palm oil plantation expansion as a causal variable. It is possible that some unobservable factors may influence both the incidence of violence and oil palm production in a particular location. For example, local property rights regimes or the strength of local institutions may be related to both violence and new investments in the oil palm sector. These factors cannot be easily captured in the data and could lead to bias in our estimates. Relatedly, palm production may not expand in areas with a very high risk of violence. Given the long-term planning required to reap rewards from the commodity, investors may be hesitant to invest in areas that have pre-existing risk factors that are likely to exacerbate violence. Due to this feedback effect from violent crime to oil palm plantation expansion, the statistical relationship between the two variables could be non-linear.

The effect of time-constant unobserved factors can be taken into account in a fixed effects regression model. Yet there may be other factors correlated with presence of oil palm that vary over time and affect trends in violence. We account for this source of confounding by ensuring that our estimates are robust to the inclusion of appropriate control variables and to the use of instrumental variables and reduced form estimation, with agro-climatic suitability for oil palm production instrumenting for actual cultivation. Oil palm requires a certain climatic and geographic conditions for it to be viable, including the slope of the land, rainfall patterns, and soil type (Pirker et al., 2016). We do not expect the degree of palm oil suitability to be correlated with unobservable influencers of violent crime, after controlling for observable characteristics of the location in the baseline.

Taking note of these issues, we perform three types of analysis:

Village level analysis: At the village level, we estimate the following regression model:

$$violence_i = \beta_0 + \beta_1 pre_i + \beta_2 post_i + \beta_3(palm_i \times pre_i) + \beta_4(palm_i \times post_i) + \alpha X_i + e_i \qquad (1)$$

where $violence_i$ is the measure of violence in location i, $palm_i$ is share of village area under oil palm production, pre_i is an indicator for *pre-boom* villages, and *post* is an indicator of *post-boom* village. Coefficients β_1 and β_2 reflect the relationship between village type and violence in general relative to *no palm* villages, while coefficients β_3 and β_4 indicate additional effect of having larger village areas under oil palm. Other relevant characteristics of the village are accounted for by including control variables X_i.

Panel data analysis: Since we can form a panel of sub-districts (*kecamantan*), we estimate the following panel data model:

$$violence_{it} = \alpha_0 + \delta palm_{it} + \sum_t \beta_t palm_{it} \times year_t + \sum_t X_{i0} \times year_t + fe_i + fe_t + e_{it} \qquad (2)$$

where, $violence_{it}$ is violence in location i at time t, $palm_{it}$ is a measure of intensity of oil palm production at time t, X_{i0} is a vector of control variables measured during baseline year (2005), $year_t$ is an indicator variable for year t, fe_i represents the fixed-effects of location i, and e_{it} incorporates other unmeasurable factors that may affect violent crime. The interaction between $palm_{it}$ and $year_t$ allows oil palm production to have different impacts on violent crime over time. We used a fixed-effects negative binomial model to account for time-invariant sub-district effects.

Year interactions: We also have annual data on incidence of violence between 2005-2014 for several Indonesian provinces, which allows us to study the dynamics of violence. To explore the timing effects around expansion, we also use the following regression specification:

$$violence_{it} = \alpha_0 + \delta palm_i + \sum_{t=2006}^{2014} \beta_t palm_i \times year_t + \sum_{t=2006}^{2014} \theta_t X_{i0} \times year_t + \sum_{t=2005}^{2014} \delta_t year_t + fe_i + e_{it} \quad (3)$$

Here, $crime_{it}$ is the violent crime incidence in location i at time t, $palm_i$ is a measure of intensity of oil palm production in the location, X_i is a vector of control variables measured during the baseline year (2005), $year_t$ is an indicator variable for year t, fe_i represents the fixed-effects of location i, and e_{it} incorporates other unmeasurable factors that may affect violent crime.[4] The estimates β_t - one for each sample year - shows the trends in violent crime in areas with varying intensity of palm oil cultivation, thus providing an impact of oi l palm expansion on violent crime. Conceptually, this model tracks the evolution of violent crime in locations with varying degrees of oil palm production. Our specification mirrors the one used by Berman et al. (2017, pg. 1574), except that we use year dummies rather than prices of minerals in that year.[5]

For each analysis, we present results from different models that vary in how $palm_i$ is measured. In the baseline model, we use area under palm production in 2005. Alternatively, we also use area under palm production measured in 2015 (the time period remains the same as in the baseline model). The latter model is used to account for the possibility that violent crime incidence may precede oil palm production. Thus areas that eventually recieved oil palm (after 2005) still may experience violent crime between 2006-2014. In the third variation, we use area with high level of suitability for oil palm production as $palm_i$ since actual production might be endogenous (Mejia and Restrepo, 2013).

For the sub-district analysis, the dependent variable is a count of the number of crime or conflict events in each location, with many locations reporting no such violence, we use a negative binomial fixed-effects regression model. We also vary the estimation sample of sub-districts to test robustness of our results.

[4]The difference between the panel model and the year interaction model lies in the choice of palm variable. In the panel model, palm production and violence are related contemporaneously, while in the year interaction models we use an oil palm variable from a single year.

[5]We only deal with single commodity - oil palm - rather than multiple minerals in Berman et al. (2017).

Our standard errors are corrected for potential correlation across sub-districts by clustering by province and time.

4.2 Data description

4.2.1 Violence data

To proxy for *extortion* and *competition* violence, we use incidence of various types of crimes and conflict reported in the NVMS and PODES datasets. NVMS records incidents of violence that are reported in local newspapers (National Violence Monitoring System (NVMS) dataset, 2015). Detailed description of the data compilation method is available in Barron et al. (2014). It defines violence as any deliberately committed actions that either (1) cause physical harm to people or property (injury, bruising, death, rape/sexual harassment, damage to buildings, broken windows, burned houses, etc) or (2) restrict physical freedom of people (abduction, kidnapping, etc). Events are classified into "resource conflict," "governance conflict," "electoral conflict," "identity-based," "popular justice," "law enforcement," "criminality," "domestic violence," "separatist," and "others."[6] *Extortion* violence is proxied by "criminality" and "law enforcement" types of violence, whereas *competition* violence is proxied by "resource related" and "identity-based" types of conflict. Although the events are recorded at the village (*desa*) level, we aggregate the information to the sub-district (*kecamatan*) level. Thus, our estimation dataset comprises of a panel of sub-districts with information on the number of violent events occurring yearly from 2005 to 2014.

The period we focus on (2005-2014) has coverage for 16 provinces containing 3,737 of the 6,771 sub-districts (based on 2011 boundaries).[7] During the 2005-2014 period, 181,134 events were recorded by the NVMS database in the 16 provinces. Criminality and popular justice are the most common types of violence, comprising over 75% of reported events. In Table A3 we show the distribution of violence/conflict type for years 2005, 2008, 2011, and 2014. We find that the distribution has changed modestly over time, with criminality reducing over the period from 65% to 59% of recorded events, while popular justice rose from 11.5% to over 15%. We also observe a rise in identity-based conflict events. Unfortunately, 14% of the events specify only the province and district where the event occurred, but not the sub-district.[8]

[6] The description of each is provided in Appendix Table A2.

[7] The 16 provinces covered by the NVMS database between 2005 and 2014 are: Nanggroe Aceh Darussalam, North Sumatra, Lampung, DKI Jakarta, East Java, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, East Kalimantan, North Sulawesi, Central Sulawesi, South Sulawesi, Maluku, North Maluku, West Papua, and Papua. Coverage was expanded to 34 provinces from 2012.

[8] We drop these events in our sub-district analysis. There may be some concern that this may systematically bias the result. In examining the type of events that tend to not have information on the sub-district location, the proportion of criminal activity is the same as those events with sub-district information. Violence related to law enforcement is overrepresented, popular justice and domestic violence are slightly underrepresented. Older events that took place before 2010 are more likely not to have sub-district information available. As long as the information is not systematically missing across palm producing and non-producing areas, our estimates should accurately reflect the difference between these two types of sub-districts.

Our second source of violence data is the Village Potential Survey (*Pontesi Desa Survei* - PODES) dataset, which is a census of all villages in Indonesia conducted at roughly 3-year intervals. We use data from PODES 2014. PODES asks respondents (usually the village head) various questions about village demographics, the economy, and other major events that occurred over the past year. A module on village security includes questions about the occurrence (as well as detailed information about parties involved) of any mass fights (*perkelahian massal*) and the occurrence of varous types of crime. We consider the occurrence of mass fights to be a proxy for *competition* violence whereas serious forms of criminal activity proxy for *extortion* violence.

According to PODES data, in 2014 about 3.4% of the villages reported a mass fight in the community, a proportion which has remained constant since 2006. Among villages that report any violence, the total number of events reported was 4,658 (1.67 events per village) across seven categories ("within community groups," "between community groups/villages," "community groups with security forces," "community groups with government officials," "students," "between tribes," and others). The first two categories comprised over three-fourths of the total events reported. Likewise, 49% of the villages reported at least one type of crime occurring in the village over the last year. Theft was the most common crime, reported by 41% of the villages, followed by gambling (13%) and fraud (9%). Violent theft was reported by 3.6% of the villages.[9]

One caveat to note with the use of PODES is that, given that this information is reported by the village head, there may be misreporting of violent episodes. The inconsistency between NVMS and PODES violence data for corresponding years has been documented by Barron et al. (2014). Their main concern, based on comparison of reported violent deaths in PODES and NVMS, is underreporting of violence in calmer areas and overreporting in areas with more violence. Thus, in addition to these two national sources of data, as described below, we also conduct a primary survey in which we collect information on individual experience and recollection of conflict and crime. Using multiple sources of violence data allows us to check the robustness of our findings to alternative data sources.

4.2.2 Oil palm data

The main variable we use to characterize the involvement of a village or sub-district in oil palm production is share of sub-district area under oil palm cultivation. This is computed using remote-sensed data that classifies pixels in satellite images as areas under oil palm cultivation (Austin et al., 2017). By overlaying the 2014 administrative boundary map layer on the map identifying oil palm production, we calculate the share of village area under oil palm production. The area can also then be aggregated up to the sub-district and

[9]The other categories that the PODES questionnaire include: "persecution," "burning," "rape/crime against decency," "murder," and "trafficking."

district levels. This gives us information on oil palm coverage area every five years from 1995 to 2015. The satellite data provides a fairly accurate measure of actual oil palm coverage when compared against official statistics.[10]

Due to the fact that oil palm trees take some time to bear fruits and become productive, and our hypothesis that involvement in production as well as actual output is related to the type of violence, we need understand the relationship between the area under oil palm cultivation and commodity production. Our supplementary analysis shows that the estimated oil palm production area in a more recent year has a weaker relationship with actual output than estimated area in an earlier period. The strongest relationship is between palm area in 2000 and production in 2010. In districts of Sumatra, for instance, one additional hectare of area under oil palm in 2010 is associated with only 2.8 tons additional output, whereas one additional hectare of area under oil palm in 2000 is associated with 4 additional tons of output. In Eastern Indonesia - where expansion was relatively recent - the difference in production between new and old areas is even starker. This is also clear from Figure A5, which shows how district-level oil palm yield (tons of output per hectare) changes with the proportion of a district's oil palm area in 2010 which was newly cultivated since 2000 and 2005. As the districts share of oil palm area which has expanded since 2005 goes up, predicted yield goes down, meaning lower level of actual production per hectare in 2010. This is because new oil palm trees are much less productive than older ones.

The summary statistics for oil palm production are shown in the Appendix (see Tables A6-A9), separately for oil palm-growing regions of Sumatra, Kalimantan, and Papua. First at the village level, Table A6 shows how villages are engaged in oil palm production over time. Across all three regions, while only 8% of villages had some of its area under oil palm production in 1995, by 2015 almost 20% of the villages had some oil palm production. In 2015, eight provinces had over a quarter of the villages in oil palm production in 2015 (see Table A6) when only one such province existed before 2000. The expansion of oil palm production was both intensive and extensive. Table A7 shows how much of village area on average was under oil palm cultivation separately for different types of villages based on first recorded instance of oil palm cultivation. Among villages in Sumatra that were already cultivating oil palm in 1995, 22% of village area was under oil palm on average. This share had increased to 44% by 2015. The corresponding change in Kalimantan and

[10]To ensure the accuracy of the satellite-based data, we check its correlation with the official statistics reported by the Ministry of Agriculture and available from the World Bank in its Indonesia Database for Policy and Economic Research (INDO-DAPOER) database (see A4). The correlation coefficient is 0.88. The graph in Appendix Figure A4 plots the correlation. The figure shows the correlation at the district-level, which is the level of disaggregation at with INDO-DAPOER is available. The advantage of satellite data is that we can use it study our research question at sub-district and village level. Another verification of the accuracy of oil palm data comes from independently sourced data on locations of oil palm mills and concession lands (Global Forest Watch). Villages with greater area under oil palm plantation coverage according to satellite data are located closer to documented mills and concession lands. As shown in Appendix Table A5, a 1% increase in distance from mills or concession land is associated with a 0.1 (10 percentage point) decrease in proportion of village area under oil palm cultivation.

Papua was from 11% of village area under oil palm to 46%. Villages that started cultivating in 2005 also had one quarter of the area under oil palm cultivation by 2015. Likewise, villages in Kalimantan and Papua that already had oil palm in 1995 continued to expand oil palm production in the 2000s. At the same time, villages that recently obtained oil palm also continue to grow rapidly (see Table A7).

We observe similar patterns when aggregating at the sub-district level. The proportion of sub-districts producing palm increased between 2000 and 2015 in all the producing provinces (see Table A8). The fastest growth is observed in Kalimantan, where the share increased from 29% in 2000 to 63% in 2015. In 2000, 30% of sub-districts in Sumatra, 29% in Kalimantan and 8% in Papua had some oil palm plantation. Over the next 15 years, as new areas came under production, the percentage had grown to 43%, 64%, and 15% respectively, highlighting the rapid growth especially in the Eastern parts of Indonesia. The fastest growth came between 2005 and 2010 in Kalimantan, where the share of sub-districts with any oil palm increased from 36% to over 53%. The coverage of palm oil also increased between 2000 and 2015. Focusing on those sub-districts which had some plantation in 2015 (thus ignoring sub-districts that never received any oil plam plantation), Table A9 shows that the amount of oil palm area has also been steadily increasing over time, especially in Kalimantan and Papua.

During our study period 2005-2014, many sub-districts experienced growth in their oil palm area. In Figure A6, we look at the relationship between sub-district's 2015 oil palm area and share of newly cultivated area since 2005. We find a negative relationship, with sub-districts with greater oil palm coverage also had most of the cultivation done prior to 2005. On the other hand, sub-districts with less oil palm area had greater proportion of recently cultivated oil palm area. These two factors are likely to exert opposite effect on our variable of interest. A wider coverage of oil palm production means more locations where conflict might arise. On the other hand, if violence is more prevalent in newer areas because of competition over new rents amongst competing groups, sub-districts with smaller oil palm coverage may be more prone to violence.

4.3 Control variables

We construct control variables from *Pendataan Potensi Desa* (PODES) and Census data. The controls include those related to social characteristics (percentage of Christian, percent migrants), economic characteristics (presence of plantation business), political situation (voting patterns), and security apparatus (distance to nearest police station). Except the social characteristics, the controls are derived from PODES 2005, which collects information at the village level. To convert a village-level characteristic into those of the sub-district, we calculate the share of households living in village with that characteristic. For example, with distance to police station, we calculate the share of families living in villages where police station is within 5 kilometers (km). A summary of all the variables used in the empirical analysis is presented in the Appendix in Table A10.

4.4 Results

In this section, we present our findings from regression analysis of the impact of oil palm production on *extortion* and *competition* violence. We begin by reporting results from our village-level analysis.

4.4.1 Village level results

Table A10 presents means and standard deviations of selected village characteristics. The first column pertains to all villages in Sumatra, Kalimantan, and Papua, while column (2) shows information for pre-boom (pre-2005) villages, and column (3) shows information post-boom (post-2005) villages. We see that palm producing villages show elevated levels of violence across all types, but the most stark difference is on the incidence of theft and violent theft, i.e., *extortion*. The summary table also makes clear that there exist other differences between villages with and without oil palm production, such as distance to the district mayor's office (post-boom villages are the furthest away), availability of police posts (post-boom villages have lowest likelihood), and presence of several ethnic groups (pre-boom villages tend to be more diverse). Some of these variables will be used as controls in the regression model.

Table 1 reports the village level estimation of equation 1 with measures of *extortion* violence as the dependent variables. Columns 1 and 2 use the incidence of theft; columns 3 and 4 use the incidence of violent theft; and columns 5 and 6 use harm (murder and trafficking) as dependent variables. We find that oil palm villages are much more likely to report experiencing crime, but that differences between pre- and post-boom village persist. The coefficients suggest that pre-boom villages are 8 percentage points more likely to report extortion violence in the form of theft and violent theft. Likewise, pre-boom villages are three times more likely to report theft than post-boom villages. The estimated impact on incidence of harm is smaller but still statistically significant. The coefficient on the share of village area under oil palm cultivation is small and statistically insignificant at conventional levels. This could be because we do not have information on the intensity of crime at the village level.[11] Consistent with our hypothesis, it remains the case that productive oil palm producing villages are most likely to report experiencing a host of *extortion*-type crimes. The consistency of this effect over time further indicates that much of the violence takes place during the

[11] As an additional analysis, we also check whether distance to nearest oil palm village matters. For villages that do not produce oil palm, proximity to producing villages fuels has mixed effects (see Table A11 in the Appendix). We find no impact on violence in villages that are closer to oil palm producing areas, but we do find that they report a greater incidence of theft. This may be due to the fact that a large part of crime associated with oil palm production takes place while transporting the fruit for processing.

production phase, when oil palm fruits need to be cultivated, harvested, and transported to the facility for processing.

Table 1 here.

Table 2 reports the results of the village level estimation of equation 1 with measures of *competition* violence as the dependent variables. In columns 1 and 2, the dependent variable is incidence of mass fights, while the number of incidents is reported in columns 3 and 4. Another difference across columns is that columns 1 and 3 only use basic explanatory variables; columns 2 and 4 includes controls for other village characteristics. We find that both pre- and post-boom villages were more likely to report higher levels of *competition* violence than non-oil palm villages which serve as the excluded base group. Furthermore, we find some differences between pre- and post-boom villages – post-boom villages are more likely to report *competition* violence than pre-boom villages. The estimates in column 2 are that post-boom villages are 1.7 percentage points more likely to report mass fights *competition*, where as pre-boom villages are 1.3 percentage points more likely to report incidence of *competition* violence. The difference is even starker when considering the number of incidents, which is higher in post-boom villages. These results indicate that *competition* violence is more likely during the expansion phase of the oil palm plantation cycle.

Table 2 here.

4.4.2 Sub-district level results

Descriptive exploration of the data shows that the incidence of violence is quite different across pre-boom, post-boom, and non-oil palm producing locations. First we summarize the average level of violence by sub-district type for the years 2005, 2011, and 2014 (see Figure A7 in the Appendix). We use the incidence of six types of violence: resource, governance-related, popular justice, law enforcement, criminal, and domestic. The distribution of all violence and conflict types across oil palm producing districts is shown in Table A12. Resource-related conflict is used as the main proxy for *competition* violence, whereas criminality is the main proxy for *extortion* violence. We first note that incidence of criminality is much higher in pre-boom sub-districts than any other types of sub-districts, even in 2005, indicating that a high level of *extortion* violence was already prevalent in areas with early participation in oil palm production. Second, the trend in incidence of criminality (*extortion*) is downwards in pre-boom and non-palm sub-districts, but not in post-boom sub-districts. The general decline could be attributed to better law enforcement over time throughout Indonesia. However, post-boom locations do not seem to have been part of this general decline. Relatedly, but not central to our analysis, popular justice also saw an upward trend in pre-boom sub-districts. At the same time, the incidence of resource conflict (*competition*) rose slightly in post-boom sub-districts between 2005 and 2011, before going down by 2014 (but still above the 2005 level).[12]

To visualize the pattern of violence by type of location during 2005-2014 period, we run a baseline model specified in Equation 3 without any controls and plot the coefficients on interactions between sub-district type and year. The coefficients are derived from fitting a fixed-effects negative binomial distribution model on the violence data and are displayed in Figure 1. Resource conflict (*competition*) and criminality (*extortion*) show the clearest sign of increasing trends in pre- and post-boom sub-districts. The incidence is much higher in the 2010–2011 period than before 2006 relative to sub-districts with no oil palm production. The pattern is relative to sub-districts with non oil palm production, so it could result from faster increase in these types of conflict in oil palm producing sub-districts or due to slower decline over time. The patterns are also distinct between pre- and post-boom sub-districts. Both resource conflict (*competition*) and criminality (*extortion*) rise faster in post-boom sub-districts. We do not see a similar pattern in the incidence of governance-related violence, popular justice, law enforcement or domestic violence. This gives us some confidence that the trend is not spurious due to greater newspaper coverage of oil palm producing areas after the boom in prices. In what follows, we discuss the estimation results of models that use as dependent variables three types of violence: resource conflict, violent crime, and popular justice.

Figure 1 here.

Panel data model: We use years 2005, 2010, and 2015[13] to construct a panel of sub-districts to apply panel data analysis. Tables 3 and 4 present results of estimating equation 2 using criminality (*extortion*) and resource conflict (*competition*) as dependent variables respectively. Column 1 is the baseline model with no controls, and Columns 2-4 control for additional sub-district characteristics as indicated. In general, the coefficients on interactions between palm production and year indicators are positive and larger, indicating that the incidence of conflict is rising over time within sub-districts.

For the case of criminality(*extortion*), the coefficient on palm production is large and statistically significant, indicating that areas with palm production record higher levels of violence. According to the baseline estimates in Column 1, an increase in oil palm area by 10 percentage points leads on average to an additional 0.23 criminal activities being recorded. This is equivalent to a 3.5% increase in criminal activity due to palm production on average. The interaction between palm production and year indicators have negative coefficients, implying that the marginal impact of palm production on criminality is falling over

[12]To reiterate, an event is classified as resource conflict if it relates to violence caused by resource disputes over land, mining, access to employment, salary, environment, etc. Popular justice pertains to violence perpetrated to respond to/punish actual or perceived wrong such as retaliation over insult, accident, debt, theft, vandalism etc. Violent crime are those incidents that are not triggered by prior dispute or directed towards specific targets.

[13]Conflict data for 2015 is taken from 2014, the last year for which the data is available.

time. So, an additional 10 percentage point palm area led to a 0.17 additional criminal activity in 2010 and 0.16 in 2014. The coefficients are similar when adding additional controls. The decline in criminal events follows the general decline in the number of criminal events being recorded by NVMS over time. This could also be a result of oil palm production expanding to more rural areas, where less population density leads to a lower number of criminal activities. Nonetheless, the estimated effect is greater than one in all years, indicating that *extortion* violence remained high in oil palm areas, but did not increase with oil palm prices.

Table 3 here.

With respect to resource conflict (*competition*), the coefficient on the level of palm production is small, negative, and statistically insignificant from zero. On the other hand, the interaction between palm production and year dummies are positive, providing suggestive evidence that the effect of palm production on resource conflict increased over time. As per the baseline estimates in column (1), the impact of a 10 percentage point increase in palm production on number of resource conflicts is close to zero on average, but increases to 0.18 additional resource conflicts in 2014. Since on average sub-districts recorded only 0.33 resource conflict in 2014, the results imply that 50% increase in the incidence of resource conflict due to oil palm production in 2014. This lends support to the theory that competition violence is positively associated with the value of the resource, which increased in both pre-boom and post-boom locations.

Table 4 here.

Year interactions: The results from estimating the model represented by equation 3 are presented in Tables 5 and 6 – for criminality and resource conflict respectively. In each table, the first column reports the result with no control variables, while subsequent columns control for additional sub-district characteristics (and their interactions with time indicators). To save space, only the coefficients on the interaction between variable and year indicators are shown. The full set of controls used is indicated at the bottom of the table.

On the incidence of criminality (*extortion*), the coefficients on palm area are large and statistically significant (Table 5). This implies that in general, sub-districts with high levels of oil palm production had a greater incidence of criminal activity. A ten-percentage point increase in oil palm area is associated with a 0.25 additional incidence of criminality. The incidence of criminality is falling over time as indicated by the negative coefficients on year interactions, but the impact remains net positive. For instance, in 2012, a sub-district with ten percentage point greater coverage of oil palm saw 0.2 [=(2.53 - 0.51)/10] additional incidents of criminal activity. The main results are robust to the inclusion of additional control variables. In sum, the incidence of *extortion* violence is higher in areas with oil palm production, although it does not change with oil palm prices.

Table 5 here.

For the incidence of resource conflict (Tables 6), the coefficients on palm area is small and statistically insignificant. However, the coefficients on the interaction between palm area and years 2008, 2011, 2012, and 2013, with the highest magnitude for 2012, are significant. This shows that the impact of palm production on incidence of resource conflict is broadly rising over time. At its peak in 2012, a ten percentage point increase in oil palm area led to a 0.29 additional incidence of resource conflict in a sub-district. The incidence of (*competition*) violence coincides exactly with the boom period for crude palm oil prices, implying that the economic value of the resource is likely to be the main driver of violence. In this sense, the results are qualitatively similar to those found by Berman et al. (2017). When adding control variables, the results are similar even though the value of the coefficients are slightly changed.[14]

Table 6 here.

We also note the overall similarity of results between the panel data analysis (Tables 3 and 4) and the year-interaction analysis. The coefficients for corresponding years are quite similar. For example, for 2014, the coefficient on palm area variable is 1.92 in Table 4 and 1.8 in Table 6. Thus, our results do not appear to be driven by model choice.

4.4.3 Robustness checks using oil palm suitability

To ensure that the above results are not confounded by the endogeneity of oil palm production, we make use of information on subdistricts suitability for oil palm production based on its agro-climactic conditions based on Pirker et al. (2016). First, we check the correlation between palm area coverage in 2015 and the suitability of sub-district for oil palm cultivation. To construct the suitability variable, each pixel of a subdistrict is classified into six levels of suitability coded from zero (lowest) to 5 (highest). We then compute the proportion of subdistrict area with various levels of suitability. Among sub-districts in our estimation sample, on average, 28% of total sub-district area is under the lowest suitability level while 9% is under highest suitability level. As expected, palm suitability is highest in Sumatra, Kalimantan and Papua. On average, 43% of the total sub-district area is under highest two level of suitability in Sumatra. The corresponding statistic is 65% for Kalimantan and 38% for Papua. Table A14 in the Appendix shows the results of regressing oil palm area in 2015 and 2005 on proportion of subdistrict area under various levels of suitability. The coefficients all have expected sign - having more area under highest level of suitability increases subdistrict's area under oil

[14]The results using popular justice as a dependent variable are shown in Table A13 in the Appendix. The results show that locations with greater share of areas under oil palm production had greater incidence of conflicts related to popular justice, but only during period after peak of commodity price boom. These incidents could be related to increased resource conflict and violent crime in the area. However, the coefficients are smaller than in the case of resource conflict, indicating that this type of conflict has relatively less association with oil palm production.

palm production, while having more area under level 1 suitability reduces sub-district's area under oil palm production. Thus suitability is a strong predictor of actual oil palm cultivation.

A sub-district's suitability for oil palm production is a natural endowment that is not affected by any political or economic factors. Thus, this variable is exogenous. Furthermore, we can be confident that the direction of causality runs from suitability to oil palm production. Likewise, it is plausible that suitability does not *directly* impact any other drivers of conflict, other than through its effect on oil palm production, thus meeting the exclusion restriction. The possible exception we note is state presence, which we control for in additional specificaitons. Thus this suitability variable is a good candidate instrument to use an instrumental variables approach to correct for endogeneity of oil palm production. Once drawback is that suitability is a constant feature of a subdistrict that does not change over time. This limits its usefulness in dynamic analysis of the impact of oil palm production.

One way we can use the suitability variable is to replace it as a regressor oil palm production in estimating equation 3 to get reduced form results. We can interpret the result of this new estimation as a study of trends in conflict in sub-districts with various levels of suitability for oil palm cultivation. A similar strategy is adopted by Angrist and Kugler (2008) to study the impact of the coca boom on conflict in rural Colombia. In that paper, due to lack of subnational-level annual data on coca production, the authors use information on initial production and growing conditions to identify regions that would be disproportionately impacted by increase in demand for coca. This time-invariant growing region dummy is then interacted with year indicators to study the impact on conflict over time.

In our case, to keep the model tractable, we construct a single suitability variable that is simply the total sub-district area under highest two levels (4 and 5) of suitability. The models otherwise remain the same. When using criminality (*extortion*) as the dependent variable, as shown in Table 7, the coefficient on suitability is positive in all cases, but larger and statistically significant when adding control variables (columns 2 to 4). These controls deal with the fact that the areas most suitable for oil palm cultivation may also be less developed regions with lower state presence. In Column 4, a ten percentage point more suitable area leads to a 0.04 more incidence of criminality in the sub-district. Furthermore, we find that the impact of suitability on the incidence of criminality is actually higher in 2013 by 0.016 additional incidents. This is in sharp contrast to a small and statistically insignificant coefficient on the interaction between palm area and year 2013 reported in Table 5, column 4. Although the general conclusion from the suitability result is also that areas with more palm production tend to have greater incidence of criminality, the dynamic pattern is different from our baseline model.

Table 7 here.

This result for resource conflict *competition* is presented in Table 8. The structure of this table is similar to Table 6. The results qualitatively are similar even though the coefficient estimates are vastly different. Sub-districts where a larger share of suitable area saw a growing intensity of resource violence between 2009 and 2013. Similar to earlier results, the peak impact is in 2012, when a subdistrict with ten percentage point grater suitable area saw a 0.08 more reported resource conflict. The estimates are smaller than those in Table 6 because the suitability measure does not predict perfectly the actual oil palm production in a subdistrict. Nonetheless, the trend of *competition* conflict over time is similar to our main results. The results are also similar when adding additional control variables, giving us confidence in our main results.[15]

Table 8 here.

The second way to use suitability information is as an instrument for area under oil palm cultivation. We apply this method to our village-level analysis. We follow a two-staged least squares approach (Wooldridge, 2016, p. 476). The first step is to run a regression of oil palm area on suitability and other village controls, and obtain predicted oil palm area in 2015 from this model. In the second step, we use predicted oil palm area and its interactions in place of actual oil palm area in estimating our regression model. The intuition is that we are only using that part of the oil palm area variable that is a linear combination of exogenous variables and thus can be consistently estimated by ordinary least squares. The standard errors are bootstrapped to account for generated regressors in the first stage. The results are shown in the Appendix in Table A16. We use the model with the full set of controls. Although the coefficients are broadly consistent with the baseline results in Tables 2 and 1, the coefficients are not statistically significant owning to large standard errors.

In the case of the sub-district analysis, because our statistical model of choice – the negative binomial distribution – does not admit a simple form of instrumental variables estimation, we follow a two-step control function approach described in Wooldridge (2015). Intuitively, a control function is a regressor that, when included in the econometric model, eliminates the endogeneity issue in principle. Since oil palm suitability explains variation in the proportion of area under oil palm cultivation, but does not appear in the main estimation equation, we can use it to create a valid control function. The first step is to run a regression of oil palm area on suitability and other sub-district controls and obtain residuals of the regression. In the second step, we control for the residuals when estimating the main equation. The results are reported in the Appendix in Table A17. When using resource conflict *competition* as the dependent variable in Column 1, we

[15] Likewise, using popular justice as dependent variable also gives us consistent results to the baseline results. The strongest impact on popular justice is found during the 2012-2014 period. See Table A15 in the Appendix.

find a similar pattern of escalating conflict that coincide with the timing of the commodity boom. We also find a growing intensity of criminality *extortion* overtime. While the coefficients are different, our general conclusion holds and is robust to any endogeneiy concerns.

5 Primary survey analysis

To ensure the robustness of our analysis to measurement error and to better understand the mechanisms behind our results from secondary data, we conducted a primary survey of 1,920 households across 180 villages of North and South Sumatra provinces. By directly obtaining information from individuals in oil palm cultivating areas, the primary study complements the analysis of secondary data presented above. The villages were randomly selected based on the following attributes: high agro-climatic suitability for oil palm production but never produced palm ("No palm" villages), high agro-climatic suitability and produced palm after 2005 ("Post-boom" villages), high agro-climatic suitability and produced palm before 2005 ("Pre-boom" villages), and low agro-climatic suitability ("Unsuitable" villages). The classification was based on area under oil palm gleaned from satellite data and suitability data as described above. The survey questionnaire was developed by the authors and implemented by a local survey agency in 2019. The questions captured a wide range of information, including a respondent's involvement in oil palm production, their experience with crime and conflict, their attitudes towards governance and democracy, etc. Additional characteristics of the village were taken from the 2014 Village Potential Survey.

We first discuss the characteristics of respondents separately for each village type (for details, see Table A18 in the Appendix). Respondents are slightly older in pre-boom villages and unsuitable villages (just over 42 years old) compared to no palm and post-boom villages (less than 41 years old). Overall, the age of respondents is 41.5 years with a standard deviation of 13 years. Respondents range from 18 to 85 years. Respondents are equally distributed across gender and 85 percent of respondents are Muslim. The proportion of Muslim respondents is lower in no palm and unsuitable villages, which have larger shares of Catholic and Protestants than average. Overall, over half of the respondents are engaged in agricultural occupation, but there is some variation across types of villages. Urban areas obviously have less involvement in farming than rural areas. Villages unsuitable for oil palm have the highest share of farmers, followed by post-boom villages, then no palm, and finally pre-boom. Combining both urban and rural areas, 15 percent of the respondents reported farming or planting oil palm in new and old palm villages. Coffee production is the most common agricultural activity in unsuitable villages. The share of respondents who are involved in rubber plantation is quite high in no palm, post boom, and pre-boom villages.[16] Consistent with previous findings (Rist et al., 2010; Euler et al., 2016, 2017), our survey confirms that palm producers produce greater revenues than other types of smallholder farmers (see Figure A8 in the Appendix). Palm farmers are more likely to be in the "high" income bracket of self-reported average monthly household income. Almost half of palm farmers fall in this bracket, compared to 30 percent of smallholders.

5.1 Results

We use a probit model to analyse the factors that effect a respondent's experience and perceptions of crime *extortion* and conflict *competition*. Most dependent variables are indicators that take the value 1 or 0, so we model the probability that the indicator takes the value 1 conditional on village type, controlling for other characteristics. Village-level characteristics include the incidence of crime and conflict in 2014, the presence of a police post within 5km, and others. Individual control variables are a male dummy, age, age-squared, education, income, economic activity (non-farmer, rice producer, coffee producer, oil palm producer, rubber producer), and an urban residence dummy. For every dependent variable, we report predictive margins of each village type. The predictive margin is the average predicted likelihood of the dependent variable taking a positive value if all villages were of a given type.

The first variable we study is the perception of different types of conflict in a village. The dependent variable is an indicator that takes value 1 if the respondent perceives that the issue is a lot, quite a lot, or quite a bit of a problem. The survey asked about the following issues: terrorism, religious conflict, ethnic conflict, group conflict, juvenile delinquency, thuggery, violence, theft, other crimes, corruption, land conflict, etc. Respondents in post-boom villages have the highest predicted probabilities for perceiving terrorism, religious conflict, ethnic conflict, thuggery, violence, and other crimes to be a major problem (see Table A19 in the Appendix, which shows the predicted probabilities of each type of issues for each type of village.

Next, we discuss the results when the dependent variable pertains to the actual occurrence of violent crime and conflict. For this we use three different measures: (1) violence or crime personally experienced or witnessed by the respondent, (2) violence or crime that occurred in the village over the past year, and (3) violence or crime that occurred in the village over the past five years. For each, an indicator taking a value 1 if the respondent answers in the affirmative. The type of violent crime and conflict considered include: (1)

[16] Although the growth in rubber has not been as dramatic as oil palm, the presence of rubber alongside oil palm complicates the interpretation of the relationship between conflict and oil palm areas. Rubber is also an important plantation crop in Indonesia and experienced a similar growth in prices during the same period as oil palm. Indonesia is the second largest rubber producer after Thailand; along with Malaysia, the three Southeast Asian countries produce 70 percent of world's natural rubber in the world. Indonesian rubber is mostly produced for exports. Four-fifths of the rubber is produced by small holders, comprising 3 million of the 3.6 million production area under rubber. North and South Sumatra provinces happen to the main rubber producing locations. In our analysis of the survey data, we distinguish between rubber producers and oil palm producers to add to the interpretation of our econometric results.

Theft of ownership of villagers' homes and garden; (2) Theft of ownership or crops; (3) Theft of a motorcycle or motor vehicle; (4) Robbery (ambush / robbery / robbery) on the road or when transporting crops, physical violence (involving 3 people or less); (5) mass physical violence (involving 4 or more people), physical violence involving blunt instruments (involving 3 people or less); (6) Mass physical violence involving blunt instruments (involving 4 or more people), physical violence involving sharp instruments (eg knives, swords) (involving 3 people or less), mass physical violence involving sharp instruments (eg knives, swords) (involving 4 or more people), physical violence involving firearms (including firearms) (involving 3 people or less), mass physical violence involving firearms (including firearms) (involving 4 or more people), violence that leads to physical injury with 1 victim, violence that leads to physical injury with more than 1 victim; and (6) Others (Domestic violence (eg a husband hits his wife), sexual violence or rape, murder with 1 victim, murder with more than 1 victim, and others).

The predicted margins for each village type on personal experience of violent crime, village-level occurrence in the past year, and village-level occurrence in the past 5 years are reported in the Appendix (see Tables A20, A21, and A22 respectively). We find that property crimes occur more frequently in oil palm villages than in non-oil palm villages. This is particularly the case for robbery (column 4) and violence (column 5), both types of *extortion* violence. We find that these crimes are more or less equally likely across pre- and post-boom villages. The most serious form of *competition* violence between groups is more likely to have occurred in post-boom villages (column 6 in the results tables).

Overall, the results from the primary survey are similar to the ones from secondary data - oil palm production tends to be associated with greater perception and incidence of violence. Consistent with our hypotheses, we find that *competition* violence is elevated in expanding plantation areas, while *extortion* violence is more common in any oil palm producing areas than non-producing ones. A possibility for the lack of differentiation in the latter result is that that the primary survey was undertaken eight after the end of the oil palm price boom, with the result that the differences between pre- and post-boom villages are not as stark as was the case in early 2010s. In other words, extensive competition violence arising due to the oil palm boom has already given way to an equilibrium level of extortion violence even in post-boom villages.

6 Discussion and Conclusion

In this paper, we study the evolution in violence and crime in response to the boom in demand for and production of oil palm in Indonesia. Our quantitative analysis finds evidence of two distinct patterns of violence. We find that oil palm production is associated with an elevated incidence of violent crime. Our multi-sited fieldwork indicated that much of this violence is driven by the dynamics of extortion surrounding oil palm production. We also find that oil palm plantation expansion and increased international demand for oil palm are associated with an increase in violent clashes among armed groups as they compete to control the sector's rents. These results runs counter to some recent research, which shows that increased agricultural commodity prices are associated with a lower incidence of conflict due to the increased opportunity cost of engaging in conflict rather than farming (Dube and Vargas, 2013; McGuirk and Burke, 2017).

We argue that in the case of oil palm specifically, violence is directly associated with specific aspects of its production process; namely, the expansive and lightly administered nature of the territory in which oil palm is produced, and the presence of choke points in its supply chain, especially in the areas of harvesting and transportation. Our qualitative investigation supports this view, which reveals the operation of "mafias" engaged in both in the theft of oil palm fruit from plantations and in racketeering activities in the transportation and processing of harvested oil palms. In this respect, the oil palm sector possesses many of the features of high-value resources and illegal commodities.

Our empirical methodology extends the work of recent reseach in economics that has attempted to estimate the causal effect of resources on conflict using subnational data on location of natural resources and conflict (Berman et al., 2017; McGuirk and Burke, 2017). The granularity of our data, however, allows us to go beyond this research in at least two crucial respects. First, by utilizing satellite data on the expansion of the commodity in question, we are able to address temporal dynamics in a way that previous research has not. Second, because oil palm requires very specific growing conditions, we are able to employ instrumental variables and reduced form estimation strategies to deal with possible confounding in the location of expansion (Mejia and Restrepo, 2013).

It has been extensively documented that crime and violence surrounding the production of an agricultural commodity is made more likely if its cultivation and processing occur in areas of low state capacity Dimico et al. (2017). The expansive nature of oil plam cultivation makes plantation areas lightly populated as we noted. Thus, there is little incentive for district level political leaders–*bupati*–to vigorously extend the state into these areas. Much recent oil palm plantation expansion has occured in on the more lightly governed island of Borneo, comprising the Indonesian provinces of North, South, East, West, and Central Kalimantan, and more recently in West Papua. However, relative state absence alone is not sufficient to engender widespread violence (Cockayne, 2016). Many parts of rural Indonesia are quite safe. This paper instead suggests that oil palm cultivation specifically leads to the development of a predatory political economy, as the short half life of FFBs along with these transportation and processing choke points generate opportunties for theft and extortion, in particular by organized violent entrepreneurs.

As we noted above, our findings bear significantly on recent research on the origins and operation of organized crime. Research has shown that the Sicilian mafia, the Cosa Nostra, had its beginnings in the orange and lemon groves of Western Sicily, as local estate managers turned extortionists, offering their services as guardians to absentee landowners (Dimico et al., 2017). Protection was often from the guardians themselves, who would burn down an estate if their demands went unmet. In the Sicilian case, as in our own, a sudden and sustained commodity boom created incentives and opportunities for violent entrepreneurs to become something more organized. Still, much as they attempted to monopolize their trade, violence was frequently necessary. We see similar dynamics in rural Indonesia, suggesting that the conditions for agrarian mafia formation are not a relic of the past, but may instead be something more common. Indeed, the link between the nature of production and the formation of protection rackets speaks to the origins of the early agrarian state itself (Olson, 1993; Sánchez de la Sierra, 2020; Tilly, 1985).

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Tables

Table 1: Probability of extortion violence by village type

	(1) Theft	(2) Theft	(3) Violent theft	(4) Violent theft	(5) Harm	(6) Harm
Post-boom vill	0.0205	0.0314**	-0.000541	0.000864	-0.00187	0.0000467
	(0.0143)	(0.0141)	(0.00580)	(0.00588)	(0.00405)	(0.00403)
Pre-boom vill	0.0745***	0.0806***	0.0203***	0.0214***	0.00921*	0.0112**
	(0.0202)	(0.0180)	(0.00702)	(0.00703)	(0.00524)	(0.00517)
Palm area 2015, Post-boom	0.0192	0.0107	0.00510	0.00467	0.00629	0.00663
	(0.0390)	(0.0383)	(0.0140)	(0.0141)	(0.00945)	(0.00934)
Palm area 2015, Pre-boom	-0.0129	-0.0164	-0.0102	-0.00987	-0.0193***	-0.0180**
	(0.0280)	(0.0268)	(0.0126)	(0.0125)	(0.00708)	(0.00703)
Vill controls:						
Dist.(km) to mayor's office		-0.0322***		-0.00510***		-0.00610***
		(0.00545)		(0.00183)		(0.00133)
Infrastr: Police post within 5km		0.0560***		0.00727***		0.00851***
		(0.00725)		(0.00258)		(0.00193)
Presence of several ethnic groups		0.0946***		0.0133***		0.00633***
		(0.0138)		(0.00307)		(0.00180)
_cons	0.360***	0.276***	0.0372***	0.0393***	0.0221***	0.0381***
	(0.00292)	(0.0283)	(0.000863)	(0.00990)	(0.000599)	(0.00613)
Controls	No	Yes	No	Yes	No	Yes
Observations	37209	37119	37209	37119	37209	37119

Source: Authors' calculation from PODES 2014.
The table shows results from regressing incidence of fights and theft on village type. All regressions include district fixed-effects, and columns 2 and 4 include additional control variables. Village boundaries are based on 2014 definitions. Sample comprises of villages in Sumatra, Kalimantan, and Papua. Standard errors clustered at the district level in parenthesis. * < .1 ** < .05 *** < .01.
(Back to Section 4.4.1.)

Table 2: Probability of competition violence by village type

	(1) Had fights	(2) Had fights	(3) Num fights	(4) Num fights
Post-boom vill	0.0153***	0.0165***	0.0309***	0.0345***
	(0.00477)	(0.00478)	(0.0118)	(0.0119)
Pre-boom vill	0.0117**	0.0125***	0.0168*	0.0198**
	(0.00494)	(0.00482)	(0.00885)	(0.00892)
Palm area 2015, Post-boom	-0.0231**	-0.0234**	-0.0589***	-0.0590***
	(0.00963)	(0.00968)	(0.0221)	(0.0224)
Palm area 2015, Pre-boom	-0.00124	-0.000355	-0.00257	0.0000863
	(0.00936)	(0.00937)	(0.0163)	(0.0165)
Vill controls:				
Dist.(km) to mayor's office		-0.00568***		-0.0133***
		(0.00170)		(0.00409)
Infrastr: Police post within 5km		0.00307		0.0122**
		(0.00200)		(0.00525)
Presence of several ethnic groups		0.0121***		0.0193***
		(0.00287)		(0.00560)
_cons	0.0192***	0.0294***	0.0309***	0.0619**
	(0.000584)	(0.00905)	(0.00108)	(0.0241)
Controls	No	Yes	No	Yes
Observations	37209	37119	37209	37119

Source: Authors' calculation from PODES 2014.
The table shows results from regressing incidence of fights and theft on village type. All regressions include district fixed-effects, and columns 2 and 4 include additional control variables. Village boundaries are based on 2014 definitions. Sample comprises of villages in Sumatra, Kalimantan, and Papua. Standard errors clustered at the district level in parenthesis. * < .1 ** < .05 *** < .01.
(Back to Section 4.4.1.)

Table 3: Panel Data estimation results on the impact of palm oil on criminality

	(1) Baseline	(2) Control 1	(3) Control 2	(4) Control 3	(5) Control 4
Palm production	2.313***	2.290***	2.260***	2.299***	2.477***
	(0.505)	(0.442)	(0.492)	(0.393)	(0.398)
Palm prodn x 2010	-0.591***	-0.497**	-0.244	-0.602***	-0.615***
	(0.218)	(0.202)	(0.298)	(0.230)	(0.169)
Palm prodn x 2014	-0.734***	-0.581*	-0.200	-0.739***	-0.994***
	(0.237)	(0.300)	(0.380)	(0.270)	(0.230)
Social	No	Yes	No	No	No
Plantation	No	No	Yes	No	No
Security	No	No	No	Yes	No
Election	No	No	No	No	Yes
N	6246	5928	6027	6027	6027

Standard errors in parentheses
* p¡.1, ** p¡.05, *** p¡.01

Source: Authors' calculation. The table show results from negative binomial fixed-effects regression with criminality as dependent variable and palm production interacted with year indicator as regressor of interest. Column 1 is the baseline model. Column 2 includes the following control variables: sub-district's share of Christians, and share of migrants. Column 3 includes controls for share of families living in villages with plantation business. Column 4 includes controls for share of families living in villages within 5km of a police station. Each controls are also interacted with year dummies. Column 5 includes controls for share of families living in villages that voted for Golkar and PDP. Sub-districts are defined based on their 2000 boundaries. (Back to Section 4.4.2

Table 4: Panel Data estimation results on the impact of palm oil on resource conflict

	(1) Baseline	(2) Control 1	(3) Control 2	(4) Control 3	(5) Control 4
Palm production	-0.100	0.193	-0.626	-0.345	0.0165
	(1.741)	(1.673)	(1.871)	(1.173)	(1.485)
Palm prodn x 2010	1.165	1.217	1.324	1.362	1.205
	(0.891)	(0.852)	(1.271)	(0.932)	(0.914)
Palm prodn x 2014	1.920*	2.203*	1.642	1.991*	1.846*
	(1.068)	(1.137)	(1.491)	(1.178)	(1.122)
Social	No	Yes	No	No	No
Plantation	No	No	Yes	No	No
Security	No	No	No	Yes	No
Election	No	No	No	No	Yes
N	1872	1767	1794	1794	1794

Standard errors in parentheses
* p¡.1, ** p¡.05, *** p¡.01

Source: Authors' calculation. The table show results from negative binomial fixed-effects regression with resource conflict as dependent variable and palm production interacted with year indicator as regressor of interest. Column 1 is the baseline model. Column 2 includes the following control variables: sub-district's share of Christians, and share of migrants. Column 3 includes controls for share of families living in villages with plantation business. Column 4 includes controls for share of families living in villages within 5km of a police station. Each controls are also interacted with year dummies. Column 5 includes controls for share of families living in villages that voted for Golkar and PDP. Sub-districts are defined based on their 2000 boundaries. (Back to Section 4.4.2

Table 5: Estimation results on the impact of palm oil on violent crime - year interactions

	(1) Baseline	(2) Control 1	(3) Control 2	(4) Control 3	(5) Control 4
Palm area	2.534***	2.382***	2.564***	2.583***	2.683***
	(0.522)	(0.640)	(0.556)	(0.611)	(0.531)
Palm area x 2006	-0.511**	-0.507***	-0.439**	-0.502**	-0.453**
	(0.201)	(0.176)	(0.189)	(0.206)	(0.189)
Palm area x 2007	-0.454***	-0.413**	-0.325**	-0.462***	-0.511***
	(0.163)	(0.193)	(0.156)	(0.155)	(0.152)
Palm area x 2008	0.0854	0.139	0.357*	0.0892	0.0896
	(0.174)	(0.220)	(0.202)	(0.172)	(0.204)
Palm area x 2009	-0.301	-0.215	-0.228	-0.349*	-0.375*
	(0.186)	(0.223)	(0.235)	(0.186)	(0.209)
Palm area x 2010	-0.419**	-0.309	-0.119	-0.446**	-0.456**
	(0.184)	(0.223)	(0.261)	(0.211)	(0.225)
Palm area x 2011	-0.396**	-0.293	-0.233	-0.433***	-0.418**
	(0.198)	(0.239)	(0.255)	(0.153)	(0.176)
Palm area x 2012	-0.517**	-0.362	-0.350	-0.569***	-0.540**
	(0.212)	(0.242)	(0.244)	(0.175)	(0.243)
Palm area x 2013	0.157	0.357	0.285	0.115	0.0322
	(0.222)	(0.244)	(0.255)	(0.224)	(0.199)
Palm area x 2014	-0.726***	-0.542*	-0.354	-0.728**	-0.960***
	(0.242)	(0.305)	(0.284)	(0.283)	(0.249)
Social	No	Yes	No	No	No
Plantation	No	No	Yes	No	No
Security	No	No	No	Yes	No
Election	No	No	No	No	Yes
N	22680	21380	21680	21680	21680

Standard errors in parentheses
* p¡.1, ** p¡.05, *** p¡.01

Source: Authors' calculation. The table show results from negative binomial fixed-effects regression with criminality as dependent variable and palm presence in 2015 interacted with year indicator as regressor of interest. Column 1 is the baseline model. Column 2 includes the following control variables: sub-district's share of Christians, and share of migrants. Column 3 includes controls for share of families living in villages with plantation business. Column 4 includes controls for share of families living in villages within 5km of a police station. Each controls are also interacted with year dummies. Column 5 includes controls for share of families living in villages that voted for Golkar and PDP. Sub-districts are defined based on their 2000 boundaries. (Back to Section 4.4.2.)

Table 6: Estimation results on the impact of palm oil on resource conflict - year interactions

	(1) Baseline	(2) Control 1	(3) Control 2	(4) Control 3	(5) Control 4
Palm area	-0.383	-0.404	-0.363	-0.365	-0.320
	(1.252)	(1.045)	(1.656)	(0.948)	(1.201)
Palm area x 2006	-0.221	-0.310	-0.631	-0.140	-0.0569
	(1.743)	(1.461)	(1.470)	(1.171)	(1.543)
Palm area x 2007	1.537	1.419	1.636	1.524*	1.582
	(1.041)	(1.046)	(1.421)	(0.875)	(1.013)
Palm area x 2008	2.306**	2.146**	2.379*	2.284***	2.294***
	(0.907)	(0.846)	(1.276)	(0.680)	(0.886)
Palm area x 2009	1.534	1.665**	0.993	1.622*	1.661*
	(1.029)	(0.785)	(1.211)	(0.893)	(0.956)
Palm area x 2010	1.316	1.453	1.334	1.449	1.371
	(1.271)	(1.043)	(1.446)	(0.893)	(1.210)
Palm area x 2011	2.537**	2.537***	2.235*	2.527***	2.509***
	(1.061)	(0.811)	(1.335)	(0.802)	(0.959)
Palm area x 2012	2.890***	3.165***	2.923**	2.942***	2.718***
	(1.066)	(0.862)	(1.238)	(0.810)	(1.011)
Palm area x 2013	2.513**	2.733***	2.303**	2.512***	2.313**
	(1.071)	(0.835)	(1.155)	(0.838)	(0.994)
Palm area x 2014	1.802	2.189**	1.335	1.929**	1.696
	(1.297)	(1.102)	(1.300)	(0.850)	(1.052)
Social	No	Yes	No	No	No
Plantation	No	No	Yes	No	No
Security	No	No	No	Yes	No
Election	No	No	No	No	Yes
N	12410	11720	11950	11950	11950

Standard errors in parentheses
* p¡.1, ** p¡.05, *** p¡.01

Source: Authors' calculation. The table show results from negative binomial fixed-effects regression with resource conflict as dependent variable and palm presence in 2015 interacted with year indicator as regressor of interest. Column 1 is the baseline model. Column 2 includes the following control variables: sub-district's share of Christians, and share of migrants. Column 3 includes controls for share of families living in villages with plantation business. Column 4 includes controls for share of families living in villages within 5km of a police station. Each controls are also interacted with year dummies. Column 5 includes controls for share of families living in villages that voted for Golkar and PDP. Sub-districts are defined based on their 2000 boundaries. (Back to Section 4.4.2.)

Table 7: Estimation results on the impact of palm oil on violent crime using suitability

	(1) Baseline	(2) Control 1	(3) Control 2	(4) Control 3	(5) Control 4
Palm suitable	0.200	0.131	0.288**	0.369***	0.399***
	(0.143)	(0.155)	(0.144)	(0.114)	(0.136)
Palm suitable x 2006	-0.176***	-0.119*	-0.136**	-0.160***	-0.134*
	(0.0556)	(0.0705)	(0.0597)	(0.0460)	(0.0743)
Palm suitable x 2007	-0.0668	-0.0369	-0.0369	-0.0823	-0.0993
	(0.0744)	(0.0828)	(0.0797)	(0.0672)	(0.0785)
Palm suitable x 2008	-0.134	-0.0914	-0.118	-0.181**	-0.164*
	(0.0890)	(0.0817)	(0.0748)	(0.0764)	(0.0947)
Palm suitable x 2009	0.0673	0.0976	0.0794	0.00796	-0.00386
	(0.0872)	(0.0763)	(0.0799)	(0.0737)	(0.0868)
Palm suitable x 2010	0.154*	0.130	0.182**	0.0918	0.0904
	(0.0817)	(0.0896)	(0.0882)	(0.0679)	(0.0821)
Palm suitable x 2011	0.0718	0.0641	0.115	0.0283	0.0322
	(0.0755)	(0.0857)	(0.0938)	(0.0746)	(0.0816)
Palm suitable x 2012	0.0388	0.0424	0.0595	-0.0319	-0.0270
	(0.0818)	(0.0921)	(0.0921)	(0.0773)	(0.0842)
Palm suitable x 2013	0.290***	0.269***	0.272***	0.215**	0.168**
	(0.0681)	(0.0817)	(0.0881)	(0.0919)	(0.0821)
Palm suitable x 2014	0.165*	0.172*	0.247***	0.125	0.0424
	(0.0843)	(0.102)	(0.0891)	(0.0935)	(0.0926)
Social	No	Yes	No	No	No
Plantation	No	No	Yes	No	No
Security	No	No	No	Yes	No
Election	No	No	No	No	Yes
N	22680	21380	21680	21680	21680

Standard errors in parentheses
* p¡.1, ** p¡.05, *** p¡.01

Source: Authors' calculation. The table show results from negative binomial fixed-effects regression with violent crime as dependent variable and percent subdistrict area with high suitability as regressor of interest. Column 1 is the baseline model. Column 2 includes the following control variables: sub-district's share of Christians, and share of migrants. Column 3 includes controls for share of families living in villages with plantation business. Column 4 includes controls for share of families living in villages within 5km of a police station. Each controls are also interacted with year dummies. Column 5 includes controls for share of families living in villages that voted for Golkar and PDP. Sub-districts are defined based on their 2000 boundaries. (Back to Section 4.4.3.)

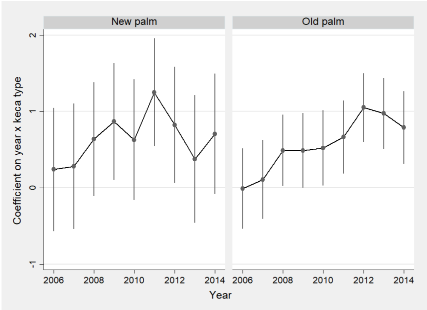
Table 8: Estimation results on the impact of palm oil on resource conflict using suitability

	(1) Baseline	(2) Control 1	(3) Control 2	(4) Control 3	(5) Control 4
Palm suitable	0.0836	-0.170	0.302	0.158	0.121
	(0.285)	(0.250)	(0.308)	(0.289)	(0.389)
Palm suitable x 2006	0.284	0.339	0.289	0.335	0.383
	(0.236)	(0.263)	(0.273)	(0.255)	(0.234)
Palm suitable x 2007	0.310	0.354	0.310	0.342	0.359
	(0.260)	(0.238)	(0.247)	(0.266)	(0.226)
Palm suitable x 2008	0.419*	0.411*	0.334	0.413*	0.444**
	(0.229)	(0.250)	(0.233)	(0.235)	(0.224)
Palm suitable x 2009	0.651**	0.752***	0.520*	0.654***	0.677***
	(0.254)	(0.249)	(0.289)	(0.251)	(0.252)
Palm suitable x 2010	0.364	0.352	0.324	0.405	0.404**
	(0.242)	(0.287)	(0.236)	(0.250)	(0.205)
Palm suitable x 2011	0.700***	0.699***	0.522**	0.646***	0.686***
	(0.219)	(0.269)	(0.209)	(0.241)	(0.197)
Palm suitable x 2012	0.801***	0.955***	0.691***	0.807***	0.738***
	(0.199)	(0.230)	(0.266)	(0.243)	(0.213)
Palm suitable x 2013	0.470**	0.540**	0.362	0.459*	0.384*
	(0.211)	(0.239)	(0.248)	(0.251)	(0.213)
Palm suitable x 2014	0.661***	0.816***	0.474*	0.633**	0.581**
	(0.194)	(0.230)	(0.267)	(0.268)	(0.232)
Social	No	Yes	No	No	No
Plantation	No	No	Yes	No	No
Security	No	No	No	Yes	No
Election	No	No	No	No	Yes
N	12410	11720	11950	11950	11950

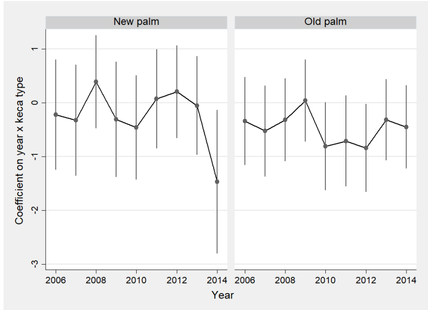
Standard errors in parentheses
* p¡.1, ** p¡.05, *** p¡.01

Source: Authors' calculation. The table show results from negative binomial fixed-effects regression with resource conflict as dependent variable and percent subdistrict area with high suitability as regressor of interest. Column 1 is the baseline model. Column 2 includes the following control variables: sub-district's share of Christians, and share of migrants. Column 3 includes controls for share of families living in villages with plantation business. Column 4 includes controls for share of families living in villages within 5km of a police station. Each controls are also interacted with year dummies. Column 5 includes controls for share of families living in villages that voted for Golkar and PDP. Sub-districts are defined based on their 2000 boundaries. (Back to Section 4.4.3.)

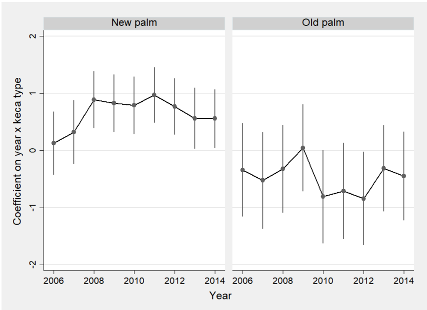
Figures



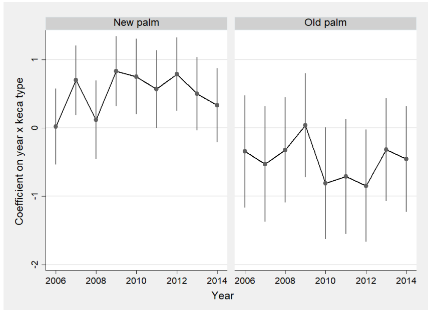
(a) Resource



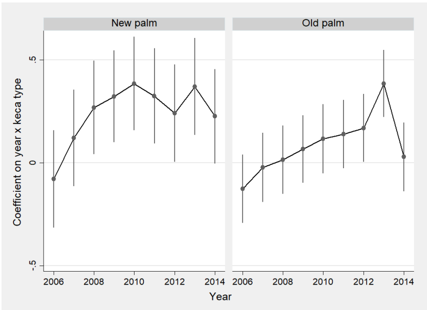
(b) Governance-related



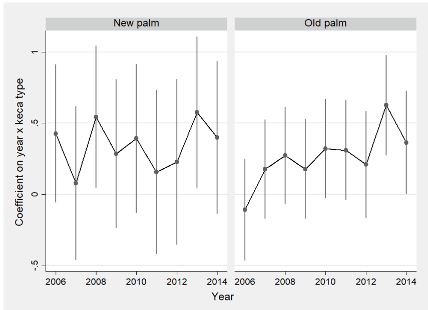
(c) Popular justice



(d) Law enforcement



(e) Criminality



(f) Domestic violence

Figure 1: Trend in various types of violence

Source: Authors' calculation from NVMS dataset. The figure plots coefficients on interaction between year dummies and indicator for type of sub-district given by fitting a fixed-effects zero-inflated negative binomial distribution model with incidence of each violence as dependent variable. Sub-districts type include: (1) no oil palm production as of 2015, (2) Oil palm production after 2005 ("new palm"), and (3) Oil palm production on or before 2005 ("old palm"), based on satellite data. Explanation of each conflict type is given in Appendix Table A2.

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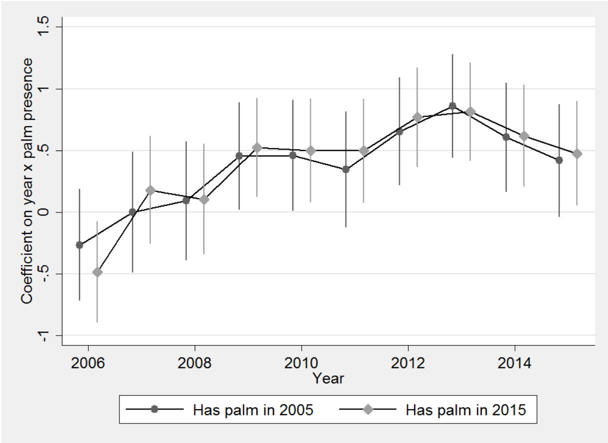


Figure 2: Trend in resource conflict by palm presence
Source: Authors' calculation. The figure shows coefficients on indicator for palm presence and year generated by a panel negative binomial regression with incidence of resource conflict as dependent variable. The lines show results from two models. In the first model, presence of palm oil in 2005 is used as the indicator of palm presence, where as in the second model, presence of palm oi in 2015 is used. The comparison is made against a baseline in 2005. (Back to Section 4.4.2.)

Appendix Tables

Table A1: Palm production area (thousand hectares) by provinces, 2011 – 2016

	2011	2014	2016	% Change 2011 to 2014	Province share 2016(% of national production)
Aceh	360.2	420.2	441.3	16.7	3.7
Sumatera Utara	1164	1396.3	1445.7	20	12.13
Sumatera Barat	370.7	376.5	399.7	1.6	3.35
Riau	1919	2290.7	2430.5	19.4	20.4
Jambi	647	693	736.1	7.1	6.18
Sumatera Selatan	873.8	923	988.4	5.6	8.3
Bengkulu	308.1	293.8	298.2	-4.6	2.5
Lampung	123.4	184.9	213.6	49.8	1.79
Kep. Bangka Belitung	186.1	206.2	218	10.8	1.83
Kep. Riau	8.7	19	20.2	118.4	0.17
Dki Jakarta	0	0	0	0	0
Jawa Barat	14.1	13.6	14.3	-3.5	0.12
Jawa Tengah	0	0	0	0	0
Di Yogyakarta	0	0	0	0	0
Jawa Timur	0	0	0	0	0
Banten	14.8	19.7	21.4	33.1	0.18
Bali	0	0	0	0	0
Nusa Tenggara Barat	0	0	0	0	0
Nusa Tenggara Timur	0	0	0	0	0
Kalimantan Barat	700.5	936.4	1455.2	33.7	12.21
Kalimantan Tengah	1008.4	1115.9	1183.7	10.7	9.93
Kalimantan Selatan	424.8	512.9	437.6	20.7	3.67
Kalimantan Timur	657.3	733.4	933.9	11.6	7.84
Kalimantan Utara	0	153.3	168.7	0	1.42
Sulawesi Utara	0	0	0	0	0
Sulawesi Tengah	93.8	147.9	157.8	57.7	1.32
Sulawesi Selatan	27.9	50.9	56.4	82.4	0.47
Sulawesi Tenggara	44.8	45.2	49.4	0.9	0.41
Gorontalo	0	4.3	12.3	0	0.1
Sulawesi Barat	95.2	106.4	111.8	11.8	0.94
Maluku	0	10.3	10.6	0	0.09
Maluku Utara	0	0	0	0	0
Papua Barat	20.1	49.6	55.5	146.8	0.47
Papua	39.5	51.4	54.2	30.1	0.45
Indonesia	9102.3	10754.8	11914.5	18.2	100

Source: Badan Pusat Statistic

(Back to Section 2.)

Table A2: Classification of conflict in NVMS data

Variables	Description
Resource Conflict	Violence triggered by resource disputes (land, mining, access to employment, salary, pollution, etc.)
Governance Conflict	Violence is triggered by government policies or programs (public services, corruption, subsidy, region splitting, etc.)
Conflict of Election and Position	Violence triggered by electoral competition or bureaucratic appointments.
Conflict of Identity	Violence triggered by group identity (religion, ethnicity, tribe, etc).
Popular justice	Violence perpetrated to respond to/punish actual or perceived wrong (group violence only)
Violence in Law Enforcement	Violent action taken by members of formal security forces to perform law-enforcement functions (includes use of violence mandated by law as well as violence that exceeds mandate for example torture or extra-judicial shooting).
Criminality	Criminal violence not triggered by prior dispute or directed towards specific targets.
Domestic Violence	Domestic violence comprises of acts of violence committed by a family member against other family member(s), where the family members live under one roof/same household.
Separatism	Violence triggered by efforts to secede from the Unitary State of the Republic of Indonesia (NKRI).
Other conflicts	Violence triggered by other issues

Source: NVMS Coding Manual.(Back to Section 4.2)

Table A3: Distribution of conflict events by type, selected years

	2005	2008	2011	2014
Other conflict	1.72	1.53	1.69	1.43
Resource	2.69	3.35	3.38	3.32
Governance	1.14	1.58	1.64	2.01
Election	0.86	1.89	1.12	2.07
Identity-based	0.69	0.79	2.98	3.29
Popular justice	11.50	11.98	14.73	15.71
Law enforcement	5.91	5.22	4.03	5.61
Criminality	64.88	63.47	60.64	58.83
Domestic violence	9.77	10.11	9.54	7.45
Separatist	0.84	0.07	0.24	0.27

Source: Authors' calculation from NVMS data. Only 16 provinces that were part of the NVMS sample during 2005-2014 period are included in the calculations. Explanation of each conflict type is given in Appendix Table A2.
(Back to Section 4.2).

Table A4: Relationship between district-level oil palm production and satellite oil palm area

	Sumatra Coefficient	Std. err.	East Coefficient	Std. err.
Palm area in 2000	4.00	0.40	4.91	0.87
Palm area in 2005	3.53	0.32	3.19	0.31
Palm area in 2010	2.81	0.29	1.55	0.17
Palm area in 2015	2.52	0.40	1.00	0.17

Source: Authors' calculation.
The table shows coefficients and standard errors from regressing district-level oil palm production in 2010 on area under oil palm production based on satellite data for the years indicated in the rows. Separate regressions were run for districts in Sumatra and those in Eastern Indonesia ("East"). All coefficients are statistically significant at 5% level. (Back to Section 4.2.2.)

Table A5: Relationship between palm area in 2015 and distance to nearest oil palm mill and concession

	(1)	(2)
	Dist to mills	Dist to conc.
Nearest distance (in logs)	-0.105***	-0.0908***
	(0.00778)	(0.00907)
_cons	0.423***	0.380***
	(0.0261)	(0.0309)
N	37173	37173

Source: Authors' calculation from satellite data.
The table shows results from regressing village oil palm area in 2015 on distance (in logs) to nearest oil palm mill and area under oil palm concession. All regressions include district fixed-effects. Distances area calculated as distance between centroids. Village boundaries are based on 2014 definitions. Standard errors clustered at the village level in parenthesis.
* < .1 ** < .05 *** < .01. (Back to Section 4.2.2.)

Table A6: Proportion of villages with palm coverage in Sumatra, Kalimantan and Papua regions by province and year

	1995	2000	2005	2010	2015
Aceh	0.03	0.05	0.05	0.08	0.09
Sumatera Utara	0.18	0.21	0.22	0.25	0.25
Sumatera Barat	0.03	0.08	0.09	0.10	0.09
Riau	0.33	0.37	0.42	0.47	0.46
Jambi	0.05	0.11	0.17	0.25	0.29
Sumatera Selatan	0.08	0.12	0.15	0.20	0.24
Bengkulu	0.02	0.05	0.07	0.10	0.14
Lampung	0.02	0.04	0.05	0.07	0.07
Kepulauan Bangka Belitung	0.07	0.22	0.25	0.30	0.35
Kalimantan Barat	0.06	0.09	0.12	0.25	0.40
Kalimantan Tengah	0.11	0.13	0.19	0.28	0.34
Kalimantan Selatan	0.05	0.06	0.09	0.14	0.17
Kalimantan Timur	0.06	0.11	0.20	0.30	0.38
Kalimantan Utara	0.01	0.05	0.06	0.12	0.16
Papua Barat	0.01	0.03	0.04	0.05	0.06
Papua	0.01	0.01	0.01	0.01	0.02
Total	0.08	0.11	0.13	0.17	0.19
Observations	36794				

Source: Authors' calculation from PODES 2014 and GIS data.
Administrative boundaries pertain to 2014 definitions. (Back to Section 4.2.2.)

Table A7: Average share of village area under oil palm in Sumatra, Kalimantan and Papua regions by province and year

	No palm	2015	2010	2005	2000	1995
Sumatra						
Palm area in 1995	0.00	0.00	0.00	0.00	0.00	0.22
Palm area in 2000	0.00	0.00	0.00	0.00	0.13	0.38
Palm area in 2005	0.00	0.00	0.00	0.09	0.18	0.43
Palm area in 2010	0.00	0.00	0.10	0.20	0.25	0.52
Palm area in 2015	0.00	0.08	0.17	0.26	0.25	0.44
Observations	24795					
Kalimantan and Papua						
Palm area in 1995	0.00	0.00	0.00	0.00	0.00	0.11
Palm area in 2000	0.00	0.00	0.00	0.00	0.05	0.21
Palm area in 2005	0.00	0.00	0.00	0.09	0.08	0.31
Palm area in 2010	0.00	0.00	0.09	0.27	0.16	0.44
Palm area in 2015	0.00	0.10	0.21	0.37	0.19	0.46
Observations	13307					

Source: Authors' calculation from PODES 2014 and GIS data.
The table shows fraction of village area under oil palm cultivation by type of the village. The columns titles indicate the first year in which the village was recorded as having palm. (Back to Section 4.2.2.)

Table A8: Proportion of sub-districts with palm production by region and year

	Sumatra	Kalimantan	Papua
Percent subdist. with palm in 2000	0.31	0.29	0.08
Percent subdist. with palm in 2005	0.35	0.36	0.10
Percent subdist. with palm in 2010	0.41	0.53	0.10
Percent subdist. with palm in 2015	0.43	0.64	0.15

Source: Authors' calculation from GIS data.
(Back to Section 4.2.2.)

Table A9: Average percentage sub-district area covered by palm production (sub-districts with non-zero palm area in 2015)

	Sumatra	Kalimantan	Papua
Palm percent 2000	12.00	2.89	1.43
Palm percent 2005	14.00	4.79	1.88
Palm percent 2010	17.82	9.67	3.43
Palm percent 2015	18.52	14.94	6.33
Observations	623		

Source: Authors' calculation from GIS data.

(Back to Section 4.2.2.)

Table A10: Summary statistics of village characteristics by village type

	(1) All villages		(2) Pre-boom village		(3) Post-boom village	
	Mean	SD	Mean	SD	Mean	SD
Conflict						
Fights	0.02	0.14	0.03	0.17	0.03	0.16
Number of fights	0.03	0.32	0.04	0.34	0.04	0.39
Theft	0.37	0.48	0.51	0.50	0.40	0.49
Violent theft	0.04	0.19	0.06	0.23	0.03	0.18
Burning	0.01	0.11	0.02	0.15	0.01	0.11
Murder/trafficking	0.02	0.15	0.03	0.16	0.02	0.15
Others	0.23	0.42	0.33	0.47	0.24	0.43
Other characteristics						
Number of families	530.07	907.65	720.79	955.08	508.17	624.92
Distance (km) to district mayor's office	56.44	84.48	66.35	59.89	72.20	78.17
Infra: electricity	83.50	28.97	92.99	15.71	85.81	22.99
Infrastr: Police post within 5km	0.49	0.50	0.42	0.49	0.36	0.48
Economy: Main inc source plantation	0.38	0.49	0.71	0.45	0.58	0.49
Presence of several ethnic groups	0.76	0.43	0.95	0.22	0.89	0.31
Observations	37209		4648		2834	

Source: Authors' calculation from various PODES 2014 data. Only villages in provinces of Sumatra, Kalimantan, and Papua that were part of the NVMS sample are included in the calculations. "Old palm villages" are those that produced oil palm on or before 2005. "New palm villages" are those that received oil palm after 2005.
(Back to Section 4.4.1.

Table A11: Probability of conflict and crime by distance to nearest palm producing village

	(1) Fights	(2) Fights	(3) Theft	(4) Theft
Dist to nearest palm vill.	0.0000861	0.000890	-0.0964*	-0.0886*
	(0.0151)	(0.0150)	(0.0495)	(0.0487)
Squared distance	-0.00131	-0.00142	0.00872	0.00769
	(0.00218)	(0.00216)	(0.00555)	(0.00539)
Controls	No	Yes	No	Yes
N	47646	47646	47646	47646

Source: Authors' calculation from PODES 2014.
The table shows results from regressing incidence of fights and theft on distance to nearest oil palm producing village. All regressions include district fixed-effects, and columns 2, 3, 5 and 6 include additional control variables. "New area" means growth in oil palm coverage by more than 5 percentage points between 2010 and 2015. Village boundaries are based on 2014 definitions, and villages in Java are excluded. Standard errors clustered at the village level in parenthesis.
* < .1 ** < .05 *** < .01. (Back to Section 4.4.1.)

Table A12: Incidence of various type of conflict by status of oil palm production

	(1) All sub-districts		(2) Has palm 2005		(3) New palm after 2005	
	Mean	SD	Mean	SD	Mean	SD
Other conflicts	0.05	0.21	0.05	0.21	0.03	0.17
Resource Conflict	0.13	0.33	0.19	0.39	0.11	0.31
Governance Conflict	0.07	0.26	0.06	0.24	0.07	0.26
Election and Position	0.06	0.25	0.04	0.21	0.06	0.25
Conflict of Identity	0.03	0.18	0.03	0.16	0.03	0.16
Popular justice	0.25	0.43	0.30	0.46	0.19	0.40
Violence in Law Enforcement	0.18	0.38	0.21	0.41	0.20	0.40
Criminality	0.59	0.49	0.70	0.46	0.56	0.50
Domestic Violence	0.21	0.41	0.27	0.44	0.20	0.40
Separatism	0.02	0.15	0.01	0.09	0.02	0.15
Any conflict	0.69	0.46	0.78	0.41	0.66	0.47
N	7580		2280		1080	

Source: Authors' calculation from NVMS data. Only subdistricts in provinces of Sumatra, Kalimantan, and Papua regions that were part of the NVMS sample are included in the calculations. Detailed defintion of conflict types is available in Appendix Table A2.

(Back to Section 4.2.)

Table A13: Estimation results on the impact of palm oil on popular justice - year interactions

	(1) Baseline	(2) Control 1	(3) Control 2	(4) Control 3	(5) Control 4
Palm area	0.932	0.629	0.152	0.778	0.565
	(0.969)	(1.312)	(1.017)	(0.913)	(0.845)
Palm area x 2006	-0.746	-0.833	-0.991	-0.865	-0.627
	(0.686)	(0.696)	(0.727)	(0.680)	(0.608)
Palm area x 2007	-0.405	-0.388	-0.501	-0.371	-0.382
	(0.665)	(0.651)	(0.568)	(0.527)	(0.626)
Palm area x 2008	0.156	0.334	0.568	0.267	0.304
	(0.565)	(0.678)	(0.574)	(0.463)	(0.465)
Palm area x 2009	0.107	0.226	0.508	0.221	0.134
	(0.607)	(0.685)	(0.662)	(0.500)	(0.475)
Palm area x 2010	0.846	0.975	1.174*	0.852	0.901*
	(0.682)	(0.700)	(0.647)	(0.574)	(0.523)
Palm area x 2011	0.428	0.641	1.047	0.545	0.468
	(0.597)	(0.716)	(0.655)	(0.515)	(0.455)
Palm area x 2012	1.382**	1.599**	1.736**	1.451**	1.409***
	(0.621)	(0.684)	(0.723)	(0.578)	(0.530)
Palm area x 2013	1.645***	1.877***	2.099***	1.668***	1.604***
	(0.553)	(0.605)	(0.566)	(0.511)	(0.526)
Palm area x 2014	1.334***	1.548***	1.895***	1.410***	1.213***
	(0.468)	(0.542)	(0.591)	(0.436)	(0.401)
Social	No	Yes	No	No	No
Plantation	No	No	Yes	No	No
Security	No	No	No	Yes	No
Election	No	No	No	No	Yes
N	16890	15970	16360	16360	16360

Standard errors in parentheses
* p¡.1, ** p¡.05, *** p¡.01

Source: Authors' calculation. The table show results from negative binomial fixed-effects regression with popular justice as dependent variable and palm presence in 2015 interacted with year indicator as regressor of interest. Column 1 is the baseline model. Column 2 includes the following control variables: sub-district's share of Christians, and share of migrants. Column 3 includes controls for share of families living in villages with plantation business. Column 4 includes controls for share of families living in villages within 5km of a police station. Each controls are also interacted with year dummies. Column 5 includes controls for share of families living in villages that voted for Golkar and PDP. Sub-districts are defined based on their 2000 boundaries. (Back to Section 4.4.2.)

Table A14: Relationship between oil palm area and suitability

	(1)	(2)
	Palm area 2015	Palm area 2005
Level 1 suitable	-0.0668***	-0.0730***
	(0.0144)	(0.0146)
Level 2 suitable	0.0447***	0.0434***
	(0.0122)	(0.0168)
Level 3 suitable	-0.00474***	-0.00480***
	(0.00124)	(0.00127)
Level 4 suitable	0.112***	0.0606***
	(0.0142)	(0.0123)
Level 5 suitable	0.0913***	0.0783***
	(0.0200)	(0.0212)
_cons	-0.00217***	-0.000794
	(0.000763)	(0.000930)
N	2384	2384

Standard errors in parentheses
* p¡.1, ** p¡.05, *** p¡.01

Source: Authors' calculation. The table show results from regressing palm area in 2015 (Column 1) and 2005 (Column 2) on proportion of subdistrict area with various levels of suitability. Level 0 suitable is omitted. Sub-districts are defined based on their 2000 boundaries. (Back to Section 4.4.3.)

Table A15: Estimation results on the impact of palm oil on popular justice using suitability

	(1) Baseline	(2) Control 1	(3) Control 2	(4) Control 3	(5) Control 4
Palm suitable	-0.0804	-0.198	0.0494	0.136	-0.0169
	(0.213)	(0.207)	(0.210)	(0.240)	(0.183)
Palm suitable x 2006	-0.171	-0.00431	-0.161	-0.187*	-0.0841
	(0.120)	(0.114)	(0.152)	(0.113)	(0.118)
Palm suitable x 2007	-0.206	-0.119	-0.251	-0.234*	-0.204
	(0.144)	(0.138)	(0.188)	(0.124)	(0.153)
Palm suitable x 2008	-0.123	-0.0226	-0.134	-0.177	-0.102
	(0.130)	(0.130)	(0.141)	(0.131)	(0.138)
Palm suitable x 2009	0.0339	0.149	0.0756	0.0189	0.0404
	(0.120)	(0.126)	(0.138)	(0.122)	(0.134)
Palm suitable x 2010	0.218*	0.284*	0.146	0.0937	0.176
	(0.126)	(0.162)	(0.144)	(0.152)	(0.135)
Palm suitable x 2011	0.284**	0.374***	0.324**	0.253*	0.264**
	(0.144)	(0.140)	(0.126)	(0.143)	(0.134)
Palm suitable x 2012	0.413***	0.503***	0.362**	0.341**	0.333**
	(0.130)	(0.132)	(0.152)	(0.149)	(0.136)
Palm suitable x 2013	0.249*	0.324**	0.221	0.179	0.118
	(0.146)	(0.144)	(0.138)	(0.146)	(0.142)
Palm suitable x 2014	0.395***	0.489***	0.413***	0.350**	0.285*
	(0.141)	(0.154)	(0.139)	(0.157)	(0.153)
Social	No	Yes	No	No	No
Plantation	No	No	Yes	No	No
Security	No	No	No	Yes	No
Election	No	No	No	No	Yes
N	16890	15970	16360	16360	16360

Standard errors in parentheses
* p¡.1, ** p¡.05, *** p¡.01

Source: Authors' calculation. The table show results from negative binomial fixed-effects regression with popular justice as dependent variable and percent subdistrict area with high suitability as regressor of interest. Column 1 is the baseline model. Column 2 includes the following control variables: sub-district's share of Christians, and share of migrants. Column 3 includes controls for share of families living in villages with plantation business. Column 4 includes controls for share of families living in villages within 5km of a police station. Each controls are also interacted with year dummies. Column 5 includes controls for share of families living in villages that voted for Golkar and PDP. Sub-districts are defined based on their 2000 boundaries. (Back to Section 4.4.3.)

Table A16: Impact of oil palm production on fights and theft - instrumental variables approach

	(1) Had fights	(2) Num fights	(3) Theft	(4) Violent theft	(5) Harm
New palm vill	-0.0121	0.0812	-0.147	-0.0154	-0.0203
	(0.0530)	(0.190)	(0.165)	(0.0659)	(0.0526)
Old palm vill	-0.0588	0.141	0.0347	-0.146	0.0783
	(0.0883)	(0.205)	(0.188)	(0.102)	(0.0861)
Palm area 2015, new palm	0.104	-0.266	0.801	0.0778	0.0976
	(0.229)	(0.820)	(0.734)	(0.293)	(0.239)
Palm area 2015, old palm	0.173	-0.295	0.0962	0.398	-0.180
	(0.211)	(0.490)	(0.461)	(0.247)	(0.207)
Vill controls:					
Dist.(km) to mayor's office	-0.00586***	-0.0130***	-0.0327***	-0.00547***	-0.00610***
	(0.000998)	(0.00240)	(0.00268)	(0.00112)	(0.000976)
Infra: Electricity	-0.0000288	-0.0000751	0.00111***	0.00000399	-0.0000571*
	(0.0000444)	(0.000127)	(0.000122)	(0.0000393)	(0.0000306)
Infrastr: Police post within 5km	0.00307*	0.0123***	0.0559***	0.00720***	0.00849***
	(0.00175)	(0.00403)	(0.00578)	(0.00225)	(0.00210)
Presence of several ethnic groups	0.0119***	0.0194***	0.0942***	0.0131***	0.00630***
	(0.00221)	(0.00578)	(0.00518)	(0.00214)	(0.00145)
_cons	0.0307***	0.0600***	0.279***	0.0418***	0.0383***
	(0.00504)	(0.0129)	(0.0167)	(0.00644)	(0.00494)
Observations	37119	37119	37119	37119	37119

Source: Authors' calculation from PODES 2014.
The table shows results from regressing incidence of fights and theft on village type. All regressions include district fixed-effects, and columns 2 and 4 include additional control variables. Village boundaries are based on 2014 definitions. Sample comprises of villages in Sumatra, Kalimantan, and Papua. Standard errors clustered at the district level in parenthesis. * < .1 ** < .05 *** < .01.
(Back to Section 4.4.1.)

Table A17: Estimation results on the impact of palm oil - control function approach

	(1) Resource	(2) Criminality
Palm area	-1.904	-0.821
	(2.694)	(0.983)
Palm area x 2006	2.626	-0.869
	(1.861)	(0.545)
Palm area x 2007	3.847**	0.537
	(1.846)	(0.562)
Palm area x 2008	4.076**	0.407
	(1.788)	(0.706)
Palm area x 2009	5.490***	1.900***
	(1.928)	(0.612)
Palm area x 2010	3.555*	2.334***
	(1.988)	(0.622)
Palm area x 2011	6.452***	1.488**
	(1.799)	(0.729)
Palm area x 2012	9.141***	1.080
	(2.047)	(0.719)
Palm area x 2013	6.625***	3.285***
	(1.892)	(0.692)
Palm area x 2014	8.407***	2.470***
	(1.863)	(0.742)
Social	Yes	Yes
N	11640	21090

Standard errors in parentheses
* p¡.1, ** p¡.05, *** p¡.01

Source: Authors' calculation. The table show results from negative binomial fixed-effects regression with resource conflict (column 1) and criminality (column 2) as dependent variables and palm presence in 2015 interacted with year indicator as regressor of interest. We add residuals from a first-stage regression of palm area on palm suitability as additional control to account for potential endogeneity of oil palm production. The model includes the following control variables: sub-district's share of Christians, and share of migrants. Each controls are also interacted with year dummies.
(Back to Section 4.4.3.)

Table A18: Characteristics of respondents

	No palm	New palm	Old palm	Unsuitable	Total
age	40.78	40.63	42.44	42.05	41.49
male	0.50	0.50	0.50	0.50	0.50
Educ:Junior	0.20	0.25	0.21	0.24	0.23
Educ:Tertiary	0.46	0.35	0.36	0.47	0.39
Inc:Middle	0.31	0.41	0.40	0.38	0.38
Inc:High	0.37	0.33	0.40	0.13	0.32
Religion:Islam	0.79	0.93	0.90	0.63	0.85
Religion:Katolik	0.14	0.03	0.07	0.28	0.10
Religion:Protestan	0.04	0.02	0.01	0.05	0.02
Religion:Hindu	0.02	0.00	0.01	0.00	0.00
Religion:Others	0.00	0.00	0.00	0.00	0.00
Religion:NA	0.02	0.02	0.01	0.04	0.02
Occ: agriculture	0.42	0.58	0.40	0.74	0.52
Rice	0.18	0.24	0.06	0.16	0.16
Palm	0.05	0.15	0.16	0.00	0.11
Rubber	0.20	0.25	0.27	0.02	0.21
Coffee	0.03	0.00	0.00	0.49	0.09
Know about Village Fund program	0.61	0.69	0.64	0.87	0.69
Talk about pol. issues with others	0.13	0.17	0.13	0.17	0.15
Satisfied with course of democracy	0.74	0.56	0.76	0.70	0.68
Agree that people cannot be trusted	0.64	0.49	0.62	0.46	0.55
Dist(km) to mill	17.81	9.63	6.65	47.23	16.27
Dist (km) to conc	41.98	30.36	30.29	72.26	39.26
Observations	1920				

Source: Authors' calculation.

Table A19: Perception of crime and conflict (predicted margins of village type)

	(1) Terror	(2) Relgconf	(3) Ethnconf	(4) Grpconf	(5) Juvenile	(6) Thuggery	(7) Violence	(8) Theft	(9) Othcrime	(10) Corrupt	(11) Lndconf
No palm	0.00856	0.00940	0.00695	0.0107	0.265	0.0757	0.0667	0.308	0.0723	0.0678	0.0430
	(0.00553)	(0.00576)	(0.00472)	(0.00535)	(0.0259)	(0.0142)	(0.0132)	(0.0263)	(0.0140)	(0.0149)	(0.0104)
Post-boom	0.0373	0.0255	0.0271	0.0496	0.214	0.123	0.143	0.326	0.125	0.0753	0.0765
	(0.00750)	(0.00581)	(0.00678)	(0.00850)	(0.0166)	(0.0138)	(0.0144)	(0.0189)	(0.0134)	(0.0110)	(0.0104)
Pre-boom	0.0224	0.0186	0.0147	0.0442	0.199	0.0778	0.0787	0.302	0.105	0.0595	0.0492
	(0.00593)	(0.00569)	(0.00474)	(0.00796)	(0.0165)	(0.0112)	(0.0117)	(0.0190)	(0.0128)	(0.00923)	(0.00841)
Unsuitable		0.00391		0.0846	0.213	0.0945	0.108	0.354	0.115	0.0773	0.169
		(0.00386)		(0.0206)	(0.0320)	(0.0226)	(0.0235)	(0.0366)	(0.0249)	(0.0199)	(0.0302)
Observations	1587	1749	1587	1917	1917	1917	1917	1917	1917	1917	1917

Standard errors in parentheses

Source: Authors' calculation.

Table A20: Personally experienced or witnessed any crime (predicted margins of desa type)

	(1) Theft_Home	(2) Theft_Crop	(3) Theft_Motor	(4) Robbery	(5) Violence1	(6) Violence2	(7) Others
Never palm	0.165	0.0893	0.139	0.0281	0.00736	0.00226	0.0897
	(0.0210)	(0.0156)	(0.0184)	(0.00819)	(0.00360)	(0.00239)	(0.0161)
Post-boom	0.203	0.0846	0.157	0.0690	0.0287	0.00690	0.134
	(0.0165)	(0.0111)	(0.0147)	(0.0104)	(0.00727)	(0.00346)	(0.0134)
Pre-boom	0.202	0.0635	0.120	0.0606	0.0180	0.00385	0.118
	(0.0168)	(0.0101)	(0.0132)	(0.00965)	(0.00565)	(0.00249)	(0.0138)
Unsuitable	0.264	0.257	0.179	0.0264	0.0223	0.0320	0.107
	(0.0325)	(0.0328)	(0.0284)	(0.0152)	(0.0131)	(0.0155)	(0.0241)
Observations	1917	1917	1917	1917	1917	1451	1917

Standard errors in parentheses

Source: Authors' calculation.

Table A21: Crime in the village past year (predicted margins of desa type)

	(1) Theft_Home	(2) Theft_Crop	(3) Theft_Motor	(4) Robbery	(5) Violence1	(6) Violence2	(7) Others
Never palm	0.292	0.155	0.371	0.139	0.0194	0.00888	0.126
	(0.0257)	(0.0203)	(0.0281)	(0.0200)	(0.00826)	(0.00432)	(0.0196)
Post-boom palm	0.279	0.117	0.276	0.109	0.0307	0.0127	0.136
	(0.0185)	(0.0127)	(0.0184)	(0.0125)	(0.00755)	(0.00413)	(0.0140)
Pre-boom palm	0.272	0.113	0.241	0.102	0.0266	0.00577	0.127
	(0.0186)	(0.0130)	(0.0180)	(0.0112)	(0.00729)	(0.00280)	(0.0145)
Unsuitable	0.307	0.310	0.248	0.0555	0.0187	0.0433	0.0825
	(0.0339)	(0.0346)	(0.0311)	(0.0205)	(0.0106)	(0.0179)	(0.0205)
Observations	1917	1917	1917	1917	1917	1917	1917

Standard errors in parentheses

Source: Authors' calculation.

Table A22: Crime in the village - past 5 year (marginal effects of desa type)

	(1) Theft_Home	(2) Theft_Crop	(3) Theft_Motor	(4) Robbery	(5) Violence1	(6) Violence2	(7) Others
Never palm	0.379	0.158	0.395	0.132	0.0367	0.00611	0.0887
	(0.0280)	(0.0205)	(0.0283)	(0.0190)	(0.0118)	(0.00374)	(0.0165)
Post-boom palm	0.324	0.148	0.310	0.139	0.0351	0.0128	0.128
	(0.0191)	(0.0140)	(0.0191)	(0.0137)	(0.00880)	(0.00441)	(0.0134)
Pre-boom palm	0.291	0.135	0.304	0.113	0.0269	0.00736	0.107
	(0.0187)	(0.0140)	(0.0196)	(0.0119)	(0.00789)	(0.00319)	(0.0132)
Unsuitable	0.371	0.334	0.273	0.106	0.0107	0.0333	0.0922
	(0.0356)	(0.0349)	(0.0322)	(0.0256)	(0.00714)	(0.0150)	(0.0202)
Observations	1917	1917	1917	1917	1917	1917	1917

Standard errors in parentheses

Source: Authors' calculation.

Appendix Figures

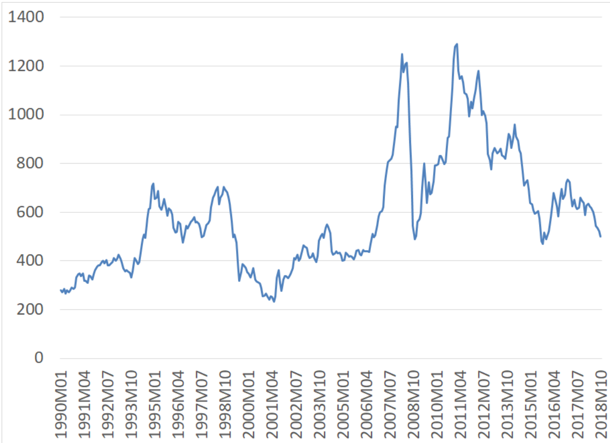
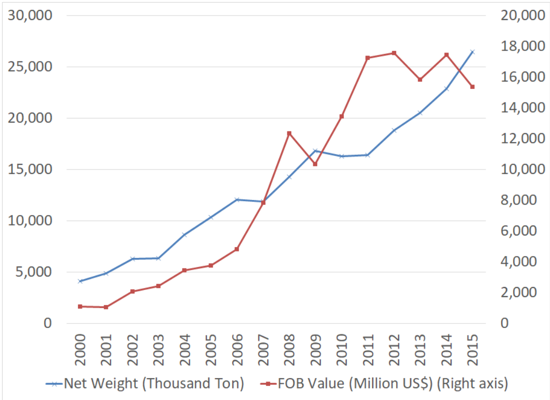
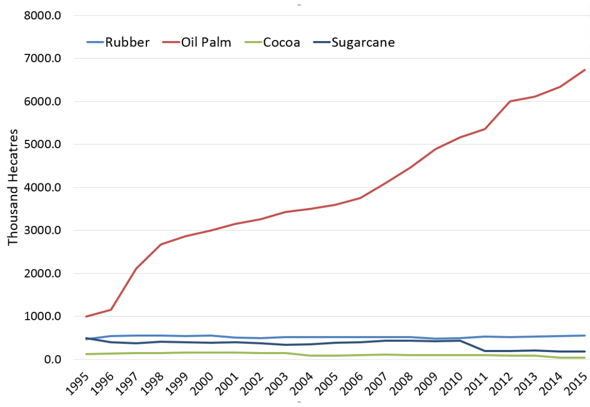


Figure A1: Monthly price of palm oil (USD per metric ton)

Source: World Bank commodity price data. The price series is for palm oil (Malaysia), f.o.b. spot beginning January 2015; previously Malaysia 5%, c.i.f. N.W. Europe, bulk, nearest forward.
(Back to Section 2).



(a) Indonesian exports of palm oil, volume and value



(b) Area under major estate crops

Figure A2: Area under palm cultivation and growth of Indonesian exports

Source: Badan Pusat Statistik. The figure shows, in thousand hectares, estate areas by major crops over time. (Back to Section 2.)

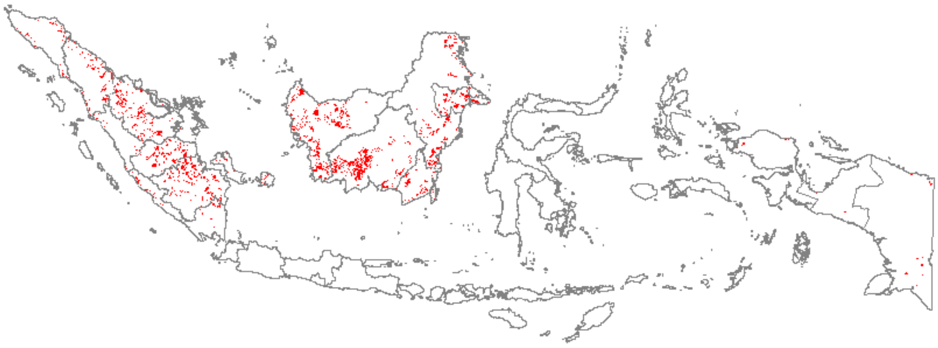


Figure A3: Growth of Palm Oil Plantation Area, 2000-2015
(Back to Section 2.)

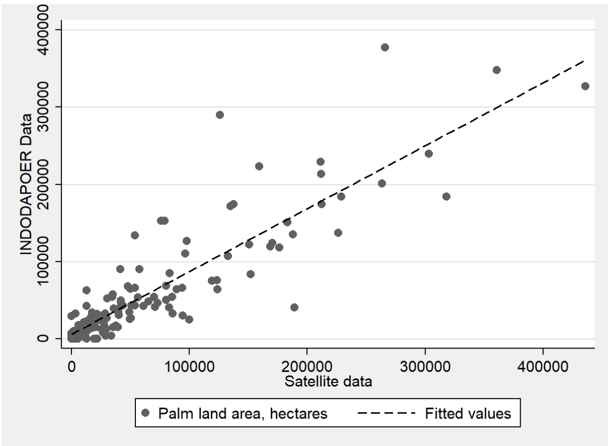


Figure A4: Correlation between district-level oil palm area in hectares from satellite data and official data. Source: Authors' calculation. Official statistics is reported by the Ministry of Agriculture and compiled by the World Bank in its INDODAPOER database. Only districts with non-zero oil palm area in the official database is included in the figure.
(Back to Section 4.2.2).

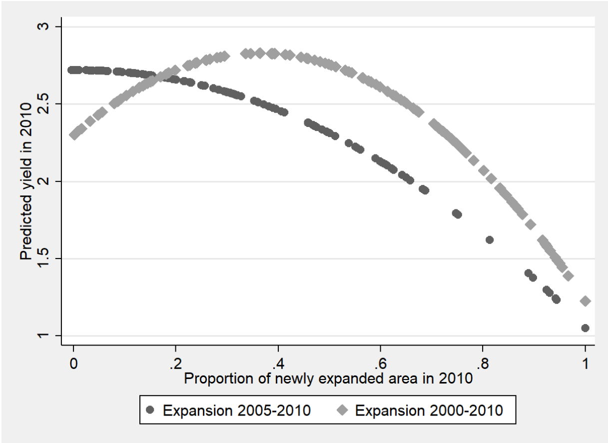


Figure A5: Predicted district-level oil palm yield

Source: Authors' calculation. The graph plots predicted values from district-level regression of oil palm yield in 2010 against the share of oil palm area in 2010 that were newly cultivated. Only districts with some oil palm area are included.

(Back to Section 4.2.2).

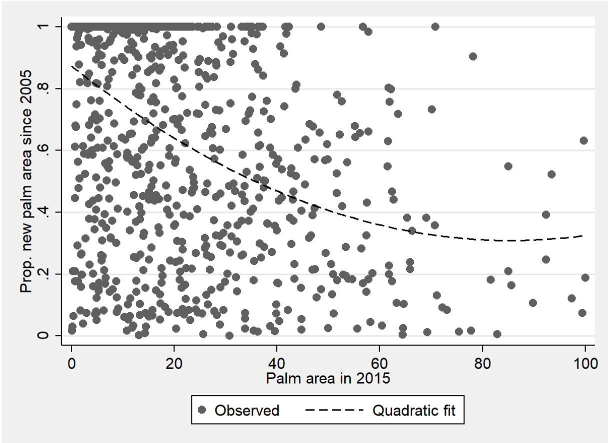


Figure A6: Sub-districts oil palm area in 2015 and new oil palm area as proportion of 2015 area
Source: Authors' calculation. The figure the relationship between subdistrict's oil palm area in 2015 and proportion of that area that was newly cultivated since 2005. Only sub-districts with non-zero oil palm in 2015 are included.
(Back to Section 4.2.2.)

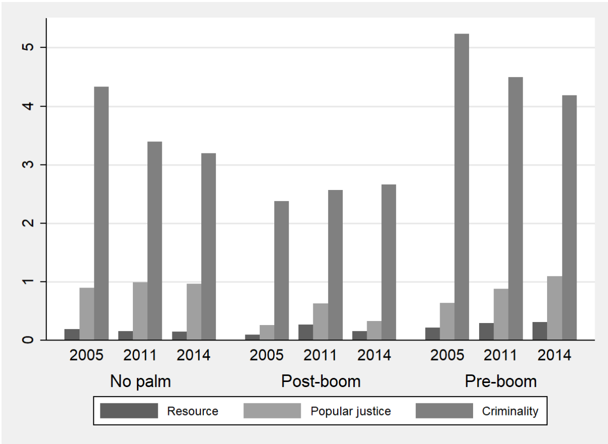


Figure A7: Average level of violence by sub-district type for 2005, 2011, and 2014
Source: Authors' calculation from NVMS data.
(Back to Section 4.4.2.)

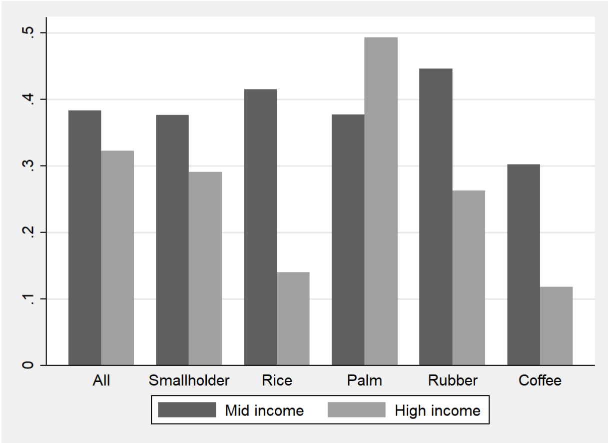


Figure A8: Self-reported monthly gross income by respondent characteristics
Source: Authors' calculation from primary survey. The figure shows proportion of respondents that fall under "middle" and "high income" bracket for full sample and also for smallholders and crop type. Middle income bracket is average monthly gross income between 1-2 million IDR and high income as above 2 million IDR. Respondents were presented with 17 income brackets to choose from. (Back to Section 5.)