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Essays on Development and Political Economics

A dissertation submitted in partial satisfaction of the

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in Management

by

Andrea Di Miceli

2017

ABSTRACT OF THE DISSERTATION

Essays on Development and Political Economy

by

Andrea Di Miceli

Doctor of Philosophy in Management

University of California, Los Angeles, 2017

Professor Romain T. Wacziarg, Chair

My dissertation studies the determinants of conflict and state formation as well as how national identities influence individuals' decisions. It consists of three chapters. The first, "Chasing the Key Player: A Network Approach to the Myanmar Civil War" studies the determinants of civil conflict in Myanmar. As governments in weak states often face several armed groups, they have to allocate resources to fight a subset of them strategically. I use a simple model to embed heterogeneity among rebel groups stemming from their network of alliances and enmities. The key insight is that, by attacking a group, the Myanmar army weakens its allies. Therefore, the model predicts that the Myanmar army strategically targets armed groups who are central in the network of alliances. To test the model's predictions, I collect a new data set on rebel groups' locations, alliances, and enmities for the period 1989-2015. Using geo-referenced information on armed groups attacked by the Myanmar army, the empirical evidence strongly supports the predictions

of the model. A one standard deviation increase in a group's centrality increases the likelihood of conflict with the Myanmar's army by twenty per cent over the baseline yearly conflict probability, thus identifying a new determinant of conflict. This result is robust to variables measuring the opportunity cost of conflict such as rainfall and commodity price shocks. Since past (and expected) conflicts might affect alliances and enmities between armed groups, I pursue an instrumental variable strategy to provide evidence that the mechanism proposed is indeed causal.

The second chapter, "Peaceful and Violent Power Consolidation: Evidence from Myanmar" analyzes how rebels' characteristics affect the Myanmar government's choice of weakening them peacefully or through military conflict from 1988 until 2015. In line with the theoretical predictions of Powell (2013), I find empirical evidence that heterogeneity in armed groups' resources and military ability affect the Myanmar government's consolidation decisions. Namely, groups whose ethnic homeland lacks resources and/or are unable to resist sustained offensives because of their limited military capacity, are more likely to be peacefully absorbed by the Myanmar government. Moreover, peaceful consolidation takes time: only three armed groups out of the forty-seven active in 1988 can be said to be completely disarmed by 2015 while almost twenty of them keep playing a role as militias linked to the Myanmar government.

In the third and last chapter, I study the cultural transmission of fertility preferences among second generation immigrant women observed in U.S. Censuses from 1910 to 1970. As hypothesized by (Bisin and Verdier, 2001), the transmission of preferences can be "vertical" or "horizontal". Using a unique source documenting the variation in fertility behavior in Europe before and after the first demographic transition (1830-1970), I unpack the influence of parents (measured by source-country fertility at the time of departure from Europe) versus the influence of peers (measured by fertility of the same-age cohorts living in the source country and transmitted by same-age recent immigrants). I find that the transmission mechanism is crucially affected by the number of foreign born immigrant peers living in the same MSA. On one hand, the "vertical" channel of transmission is stronger in places where there are few newly arrived foreign born immigrant couples from the same source countries. On the other hand, fertility choices of second generation women are strongly correlated with marital fertility choices measured over peer cohorts in the source countries whenever they live in MSAs densely populated by recently arrived immigrants.

The dissertation of Andrea Di Miceli is approved.

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2017

I want to thank all of you who took the time to listen, criticize, play and eat with me during these six short years. I am grateful for what you taught me and for how you made me a better person. Pierluca and Elia stand out from this crowd as they had the remarkable skills to stick around for longer.

Questa tesi è dedicata ai miei genitori, mia sorella e mio zio.

Voi, attorno a cui son cresciuto, mi avete stimolato, sostenuto ed incoraggiato non senza sacrifici personali. Il più grande dono che mi avete dato è stata la libertà di scegliere cosa fare della mia vita professionale. Essendo conscio dei miei limiti e difetti, mi sento fortunato perché so che sulle vostre spalle ho potuto vedere e raggiungere orizzonti altrimenti impossibili.

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Chapter 1

Chasing the Key Player: A Network Approach to the Myanmar Civil War

1.1 Introduction

Governments in weak states often face more than one armed group opposing their efforts to monopolize violence. Data show that in more than 90% of countries experiencing civil war governments have had two or more distinct armed groups to fight.[1] This fact implies that a government embroiled in civil war faces a complex decision on allocating resources to fight enemies. Recent theoretical work has shed light on the incentives for a central government to consolidate power depending on the characteristics of armed groups (Powell (2013)). However, the empirical literature has suffered from the lack of data and methodology that embeds armed groups' heterogeneity in a tractable framework yielding testable predictions.

In this study, I analyze the choice of the central government to attack rebels in its periphery. To do so, I focus on the longest civil war of the contemporary period: the Myanmar conflict. The country represents an ideal environment to study how its central government's army, henceforth denoted with its anglicized Burmese name of Tatmadaw, uses conflict to expand control over its vast frontier. In fact, the Myanmar civil war is an attempt to consolidate power in which the Tatmadaw faces multiple enemies at the same time.

I provide empirical evidence showing that the decision of the Myanmar army to attack a particular armed group is based on the complex web of alliances and enmities that exist between armed groups. This mechanism relies on the idea that the ability of armed groups to withstand a military offensive from the Tatmadaw increases in the number of allies and decreases the more enemies an armed group has. Therefore, attacking an armed group has two effects: it weakens the group itself (direct effect), but it also weakens its allies and emboldens its enemies (indirect effect). The interplay of these two

[1] This statistic has been computed using data covering the period 1989-2015 from the UCDP/PRIO Database (Croicu and Sundberg, 2015).

effects drives the Myanmar army's decision of which groups to attack over time. I use the observed cross-sectional and longitudinal variation in armed groups alliances and enmities to test predictions from the model. Namely, a network statistic summarizes which groups are more likely to be attacked in light of their network of alliances and enmities. The network statistic is the key explanatory variable in an OLS regression that sheds light on the attacks of the Tatmadaw against armed groups in the period 1989-2015.

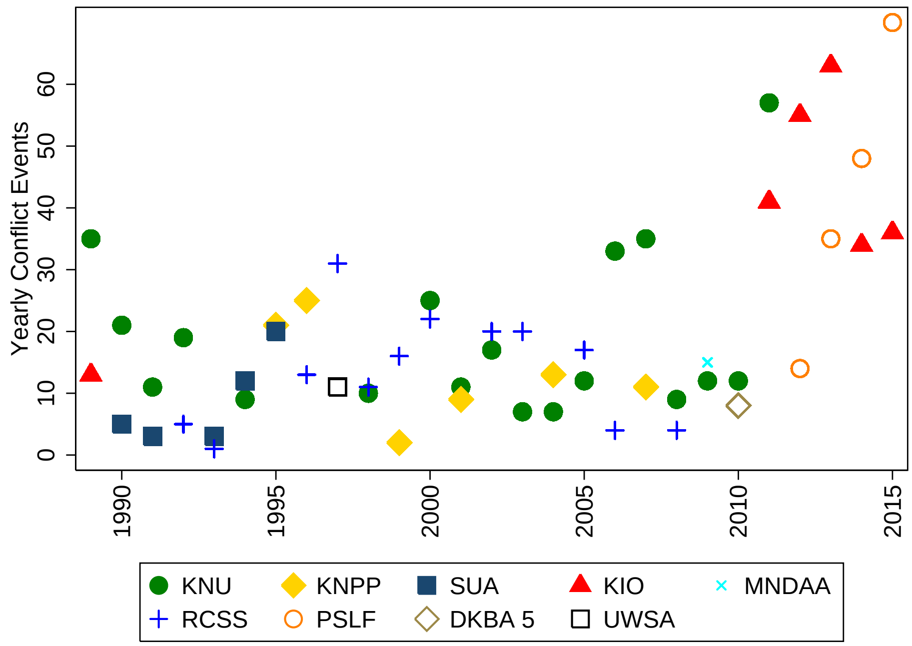
Figure 1.1 shows the yearly variation in the top two armed groups attacked by the Myanmar army and their respective number of conflict events during the period 1989-2015 (there are forty-seven active armed groups over this period). The patterns of Figure 1.1 are in line with two stylized facts of civil wars which are: (i) there are periods of persistent fighting and, (ii) fighting sometimes recurs after periods of peace.[2] This evidence further supports analyzing Myanmar as a representative case study.

My empirical analysis is derived from the predictions of a formal model. I take the onset of civil war as given and use a model to better understand how the Tatmadaw targets its fighting effort. In the model, the Myanmar army faces several armed groups with heterogeneous defensive capacity. The defensive capacity of a group represents its ability to withstand an offensive from the Tatmadaw. Every armed group is a node in the network of alliances and enmities.[3] The defensive capacity of a group is rooted in the network structure through alliances and enmities in a fashion similar to Ballester et al. (2006). Namely, the defensive capacity of a rebel group increases in the defensive capacity of its allies and decreases in the one of its enemies. Historical evidence shows that alliances benefit a group's defensive ability in several ways: allies provide supply lines for weapons, guarantee shelter outside a group's territory during offensives from the Myanmar army, and allies are often trading partners. Historical records and anecdotes confirm

[2]See Powell (2012) for a discussion on the stylized facts of civil wars.

[3]In every period, armed groups observe the network structure and non-cooperatively maximize their defensive capacity.

Figure 1.1: **Yearly Variation in the Top Two Armed Groups Fought by the Myanmar Army**



Source: UCDP 3.0 Georeferenced Event Dataset and Myanmar Peace Center Records. The armed groups in the picture are, respectively, the Karen National Union (KNU), Shan United Army (SUA), Myanmar National Democratic Army (MNDAA), Palaung State Liberation Front (PSLF), Karenni National Progressive Party (KNPP), Kachin Independence Organization (KIO), Restoration Council of Shan State (RCSS), United Wa State Army (UWSA), Democratic Karen Benevolent Army (DKBA 5).

that the Myanmar army is aware of the network structure. I capture this insight by modeling the Tatmadaw's choice of which armed group to attack according to an optimal rule that takes into account the network structure between armed groups. The optimal rule is to remove an armed group so as to reduce the overall defensive capacity of all armed groups in the network. For instance, attacking an armed group who is the main weapons' provider to other armed groups inherently damages the overall defensive capacity in the network. In particular, I use the network statistic called *intercentrality* that measures, for each armed group, the combined direct and indirect effect on the overall fighting ability associated with their removal from the network.[4] The model predicts that the Myanmar army targets groups with higher intercentrality parameter.

To derive predictions from the model and explain the pattern of violent outbreaks in Figure 1.1, I collected a new dataset of armed groups' individual characteristics from various sources documenting their alliances and enmities from 1989 until 2015. The network displays both cross-sectional as well as temporal variation. I organize the empirical analysis in two steps. In the first step, I show a positive and robust correlation between armed groups' intercentrality and conflict through a linear probability model. In the second step, I address identification concerns through an instrumental variables (IV) estimation.

I use information on armed groups attacked by the Myanmar army and the location of clashes available for the period 1989-2015 from the UCDP Georeferenced Event Dataset ((Croicu and Sundberg, 2015)) and Myanmar newspapers' records. I identify the effect of a group's intercentrality on conflict from the longitudinal and cross-sectional variation in the network of armed groups. Results based on a linear probability model show that a one standard deviation increase in a group's intercentrality over a year increases the expected probability of violence in any of its cells by 1.2 percentage points over a baseline annual probability of 6.4%. This effect is highly significant and robust to the inclusion of variables affecting the opportunity cost of fighting. To control for geographical shocks that may influence the incentive to fight, I collect data on territories controlled by armed groups, on natural resources therein and rainfall variation over time. All these variables are relevant in the context of Myanmar, a country rich in natural resources that relies mostly on rain-fed agriculture.[5]

[4]The intercentrality measure is strictly related to the Katz-Bonacich network centrality (Bonacich, 1987). This centrality measure counts the number of all paths stemming from a given node, weighted by a decay factor. Intuitively, it is a measure of information diffusion over the network, nodes with higher Bonacich centrality can spread more information over the network.

[5]In examining the determinants of civil wars, variables affecting the opportunity cost of fighting have received considerable attention. Several studies have shown that weather shocks are correlated with out-

The main concern affecting the proposed identification strategy is that the positive correlation between a group's intercentrality and attacks by the Tatmadaw might be driven by unobservable characteristics that vary systematically at the armed group level. Moreover, past conflict (or the expectation of future conflict) can lead a group to form (or strategically break) its alliances, in which case there is reverse causality. I pursue an IV estimation to address identification concerns and provide evidence that the positive relation between intercentrality and conflict is indeed causal.

The IV estimation is implemented in three steps. In the first step, I predict a counterfactual network structure using only exogenous variables that are not affected by past conflict. In the second step, I compute the intercentrality parameter from this counterfactual network. In the third step, I use the counterfactual intercentrality parameter as an instrument for the observed one to implement a two-stage least squares (2SLS) estimation. Since the intercentrality is a non-linear function of the network structure, the 2SLS estimation allows me to control transparently for variables that directly impact both conflict and the observed network structure.

In the first step of the IV estimation, I use an empirical model of network formation to predict a counterfactual network that is not affected by omitted variables bias.[6] That is, I assume that the observed relationships between armed groups stem from the maximization of their joint utility. The network formation model estimates the parameters explaining the decision to form or break alliances (as well as enmities and neutral relationships) over time. Therefore, the estimated parameters are used to predict the counterfactual network over time. Variables included in the network formation model

breaks of violence in regions that rely on rain-fed agriculture. Recent contributions to this topic are: Harari and La Ferrara (2015) and Vanden Eynde (2016). For a recent review see (Burke et al., 2015). Similarly, shocks to the price of commodities have been used to investigate their causal effects on conflict.See (Bazzi and Blattman, 2014), Berman and Couttenier (2013) as well as Dube and Vargas (2013), and Besley and Persson (2011) for recent studies reaching different conclusions on the effect of commodity price shocks on conflict.

[6] The empirical model follows the contribution of Graham (2015).

are of two types: pre-determined and time varying. Pre-determined characteristics such as the distance between ethnic homelands and linguistic proximity enter the network formation model and play a major role in explaining the decision to form an alliance (or an enmity). However, these variables are fixed over time and therefore cannot explain the longitudinal variation in the network structure. To ensure that the counterfactual network structure varies over time, I use fluctuations in the world price of resources within groups' ethnic homelands. I argue that the value of forming an alliance (or an enmity) shifts over time because fluctuations in the value of resources within ethnic homelands drive the incentives of armed groups to form and break alliances motivated by trading interests. For instance, rebel groups whose ethnic homelands have copper but lack access to the border might find profitable to form an alliance to transport the commodity from their ethnic homelands outside the country once its price is sufficiently high.

In the second step, I compute the intercentrality parameter of the counterfactual network. Given the extensive evidence on the direct impact of resources on conflict, the empirical network formation model raises the concern that these variables are not excludable when estimating the network structure (because they might also have a direct impact on the probability of conflict). However, the non-linear nature of the intercentrality parameter allows the inclusion of resources' presence and their fluctuations when estimating the 2SLS. Therefore, the 2SLS estimation controls for variables that might have a direct impact on the probability of conflict.

Estimates from the IV confirm the prediction of the model and the magnitude of the OLS findings: a one standard deviation increase in an armed group's instrumented intercentrality is associated with an increase in the expected probability of violence occurring in its territory by 1.36 percentage points over a year. That is, the Tatmadaw takes into consideration the complex web of alliances when deciding which group to attack during the last twenty-seven years. Moreover, the mechanism presented has a sizable impact on conflict when compared with the effects of weather and commodities' shocks. The expected increase in the probability of conflict caused by a one standard deviation increase in a group's intercentrality is more than twice the effect observed for a one standard deviation increase in teak wood price, the commodity with the most sizable impact on conflict in the data. Similarly, the effect of a drought is roughly eighty percent the size of a standard deviation increase of a group's intercentrality.

This paper contributes to the literature studying the determinants of civil war. The importance of alliances and enmities in conflict has been highlighted by König et al. (2016) who show the effect of inter-group relationships in escalating or reducing conflict during the Congo civil war. In my analysis, alliances and enmities between armed groups are motivated by trading patterns and mutual economic interests that go beyond military assistance on the battlefield. Therefore, this paper differs from theirs as it studies how the heterogeneity in the network of alliances (and enmities) generates an incentive for the Myanmar army to attack only some of the several armed groups present in the country.

The findings in this article contribute to the study of civil war as a tool for power consolidation. In his recent theoretical contribution, Powell (2013) argues that both peaceful and violent power consolidation are optimal choices of a dynamic bargaining game in which the government aims to extend its monopoly of violence over a rebel group. The author contends that the government's choice to peacefully buying off the rebel group rather than fighting it depends on the individual characteristics of the group such as the presence of resources in its homeland and its military strength. I argue that, by providing a simple framework that embeds armed groups' heterogeneity, this paper shows preliminary evidence that conflict is the result of a rational decision process in line with the one described by Powell (2013). While the effort to control the nation's peripheries is at the core of state formation, this process has often occurred in the remote past or in polities in which the absence of data impeded a formal analysis (Tilly (1985)).[7] This paper provides evidence on how this process developed during the last three decades in Myanmar.

Since Myanmar has more than one hundred ethnic groups, this work is also of interest to the literature debating the role of ethnicity in conflict. In the empirical model of network formation, I show that linguistically similar groups are likely not to be neutral to each other. This evidence is consistent with findings showing that more closely related populations are more likely to engage in conflict (Spolaore and Wacziarg (2016)) as well as with papers showing that ethnic polarization might lead to conflict Esteban et al. (2012).

The remainder of the paper is organized as follows: section 1.2 provides background information on the Myanmar context, the model is presented in section 1.3. Section 1.4 discusses how the dataset was built and section 3.5 shows correlations and discusses the identification problems. Section 1.6 discusses the logic behind the IV and shows that estimates are consistent with OLS ones. Section 1.7 summarizes the findings, discusses external validity and concludes.

1.2 Background: Civil War in Myanmar

Only the Tatmadaw is mother,

Only the Tatmadaw is father,

Don't believe what the surroundings say,

Whoever tries to split us, we shall never split.

[7] On the lack of data to study state formation see also Scott (2009). Sánchez de la Sierra (2016) is a notable exception as it studies the incentives leading to embryonic state formation during the great Congo War. My work is complimentary to his because investigates the use of conflict for the purpose of power consolidation.

We shall unite forever.[8]

Myanmar is a country located in South-East Asia; its land mass is comparable to Texas. The country's borders are virtually the same since the British colonized it in 1886. As shown in Figure 1.2, Myanmar's location is strategically important as it borders the two South Asian countries of Bangladesh and India on its west side as well as China on its North-East. The country is also connected to Laos to the east and shares the entirety of its Southeast border. Myanmar is ethnically diverse which can be gauged from the variety of languages spoken therein (Figure 1.2). The Bamar (or Burmese), depicted in yellow in Figure 1.2, are the country's dominant ethnic group making up roughly sixty-five percent of the total population. The Bamar occupy the core of the country while more than one hundred and thirty ethnic groups live in its vast "periphery".[9] In what follows, I detail the evolution of the civil war with a particular focus on the period between 1989 and 2015 as this is the time frame of interest for the empirical analysis.[10]

Myanmar obtained independence from the British in 1948. In the immediate aftermath, the country experienced all different forms of intergroup violence. In fact, the Communist Party of Burma (mostly made up of ethnic Bamar) rebelled shortly after independence while the first ethnic group to revolt against the central government were the Karen in 1949. Moreover, the country was also invaded by the remnants of Yunnan's Kuomintang in 1950. The constant threats and the multiplicity of internal and external enemies caused the Tatmadaw's power to grow up to the point where the army was *de facto* substituting the elected government. In 1962, General Ne Win, the highest ranked army official, seized power and ruled the country through a one-party state until 1988.

[8] Tatmadaw slogan appearing on media in the early 1990s.

[9] Scott (2009) discusses the difficulties associated with defining ethnic groups in Myanmar.

[10] A complete account of the history of civil conflict in Myanmar since its independence is beyond the scope of this work. There are several authoritative histories of Myanmar, among the many, Callahan (2004), Smith (1999) and Lintner (1999) provide excellent accounts of what happened in the country from the end of WW II to the end of the twentieth century.

Following the coup, the Tatmadaw entirely disenfranchised the non-Bamar ethnic groups, causing the sprawling of ethnic armed groups. Indeed, many border areas were (and in many cases still are) under control of ethnic armed groups with the Tatmadaw being unable to access them. In regions where Bamar do not represent the ethnic majority the Tatmadaw controls the larger cities and major roads. Figure 1.3 shows the areas under control of the armed groups in 1989 with each color being associated with a different armed group. A quick comparison with Figure 1.2 confirms that armed groups' control areas are largely confined to areas of the country where non-Bamar ethnic groups reside.

Ideology was another salient determinant of armed groups formation. Since the 1970s, two main coalitions opposed the Tatmadaw regime: the Communist Party of Burma (CPB) and the National Democratic Front (NDF). The CPB was heavily financed by Mao's China. At the height of its power, in the late 1970s and early 1980s, the CPB controlled the entire border between Myanmar and China. While Communist ideology was the glue that kept together this ethnically diverse alliance, most battalions were organized along ethnic lines Lintner (1990). Armed groups belonging to the NDF were also organized along ethnic lines and fought for federal representation (i.e. not to secede from Myanmar). Occasionally the same ethnic group had multiple armed groups as a legacy of a feudal system which existed during the British rule. For example, armed groups' formation in Shan state, the region bordering Thailand, Laos, and China depicted with turquoise in Figure 1.2, started along feudal lines as feudal lords received administrative autonomy over territories from the British colonial administration Yawnghwe (2010). Armed groups in both blocs are politically motivated and benefit from support of the population within their ethnic homeland. Indeed, taxation of villagers belonging to the same ethnic groups constitutes a common source of funding for all ethnic armed groups. For this reason, armed groups move within their ethnic boundaries, and it is unlikely to observe them in territories far from their ethnic homelands. To legitimate support from villagers, rebel groups act as providers of public goods such as education, justice and occasionally health care (Jolliffe, 2015).

The Myanmar army has always perceived armed groups as hostile to the country's unity: Smith (1999) provides an account of how the Tatmadaw perceived the ethnic armed groups: "The map of Burma was divided into a vast chessboard (...) and shaded in three colours: black for entirely insurgent-controlled areas; brown for areas both sides disputed; and white for areas free of insurgents. The idea was that each insurgent-coloured area would be cleared *one by one*, until the whole map of Burma was white. For the black areas and brown guerrilla zones, a standard set of tactics was developed which, after a little refinement, has remained unchanged until today." Since the nineties, the Tatmadaw attacked different ethnic groups as depicted in Figure 1.1. Namely, these armed groups have been attacked through "scorched earth campaigns" against the population that supported them. Indeed, the Tatmadaw applied its famous "*four cuts strategy*" which aimed at removing armed groups' support by the population and *their allies*. Several historical facts, confirm that the Tatmadaw knew about the existence of alliances and enmities between ethnic armed groups. The Tatmadaw shaped its decision to attack groups based on how influential they were (or are) in mobilizing its allies outside the battlefield. For instance, in the mid-eighties, some members of the NDF launched joint operations together with CPB against the Tatmadaw. Smith (1999) and Lintner (1999) account that the Tatmadaw was worried by the new alliance and launched a massive offensive against two of its prominent members. Other authors stress the importance of alliances and enmities when discussing the Tatmadaw's decision to attack the various armed groups in the country. For example, Oo and Min (2007) discuss what led the Myanmar army to attack the Restoration Council of Shan State through a scorched earth campaign in the mid-nineties "*(...) despite the RCSS request for ceasefire talks, the Myanmar Army has always refused them (...) seeing how dangerous the alliance between the RCSS, SSNA and SSPP* *was.*".[11] Similarly, Smith (1999) and Lintner (1999) describe the Shan United Army as the "head" of an alliance between several different groups that became too dangerous for the Tatmadaw to tolerate at the beginning of the nineties.

Alliances and enmities among armed groups are not only based on military and political considerations but also on economic grounds. Armed groups whose ethnic homelands are suitable for opium cultivation but far from the border with neighboring countries need to sell their harvest to a group specialized in trading opium abroad. In another example South (2008) mentions how a meeting between three armed groups in Kachin state to settle disputes on the logging concessions across their boundaries triggered a reaction by the Tatmadaw against the group with the largest network of alliances among the ones involved.

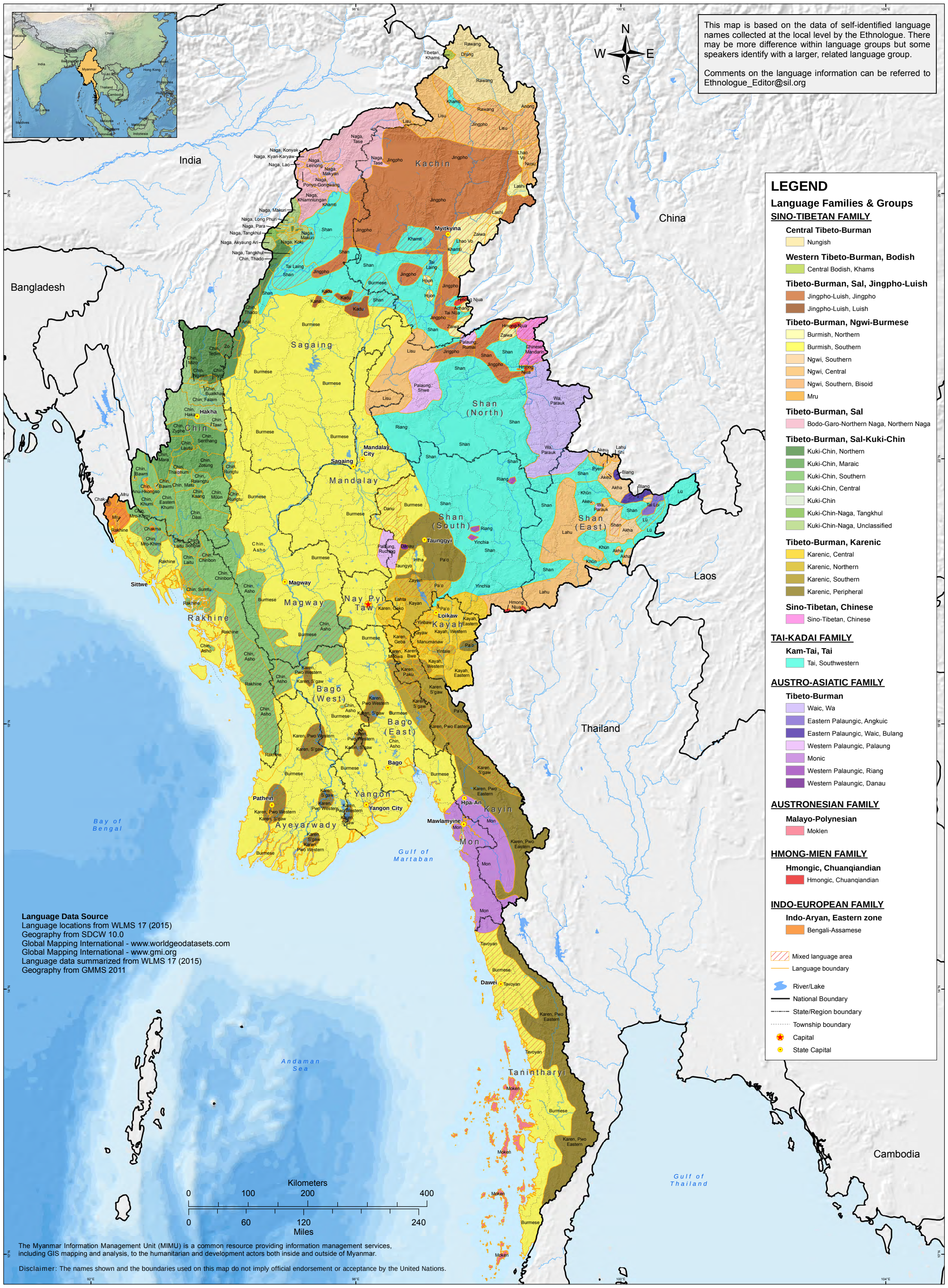
In 1988 and 1989 two events, unrelated to each other, shaped the history of Myanmar. First, following the worsening economic conditions in the country, starting in March 1988 students and civilians in the main urban centers protested against the military asking for political reforms. After a violent crackdown, a coup orchestrated by army officials forced General Ne Win to hand them the power so that the Tatmadaw retained the power. Second, in 1989 ethnic battalions within the CPB mutinied against the CPB politburo and organized themselves into independent ethnic armies. The mutinies took the Myanmar army as well as its allies by surprise. Indeed, the CPB and the Tatmadaw confronted each other on the battlefield until 1988 and the CPB still controlled most of the border with China when the mutinies occurred. The network of armed groups in the country, as well as their alliances and enmities relations, is depicted in Figure 1.4. A thin (blue) edge between nodes labels an alliance while a thick (red) edge signals the presence of an enmity between groups.

In recent years the country adopted a new constitution (2008) and had two parliamen-

[11] The same anecdote is found in Smith (1999).

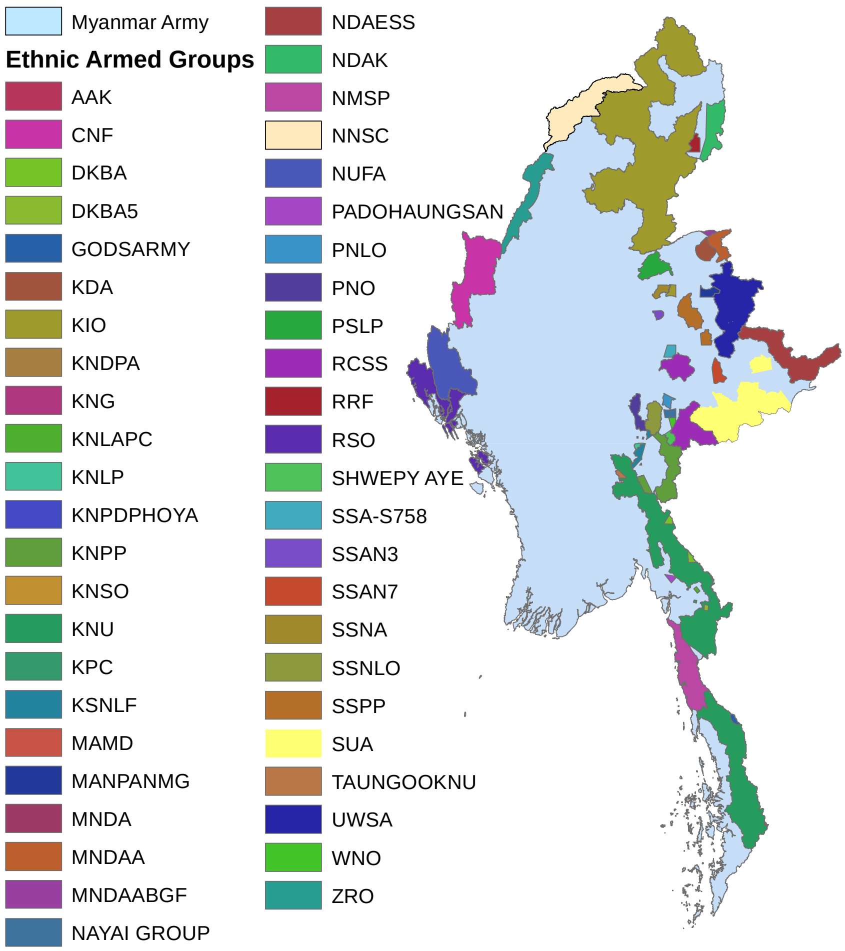
tary elections in 2011 and 2015. The Myanmar army has 25% of the seats reserved in the parliament so to veto any constitutional reform by the civilian government. Despite the transition, violence between ethnic armed groups and the Tatmadaw has continued.

Figure 1.2: **Main Spoken Languages of Myanmar**



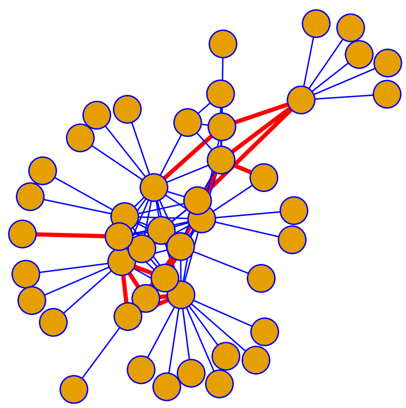
Source: Ethnologue $XVII^{th}$ eds.

Figure 1.3: **Areas under Control of Armed Groups in 1989**



The Figure shows territories controlled by armed groups at the beginning of 1989

Figure 1.4: **Network of Armed Groups at the end of 1989**



Each node represents an armed group. Alliances depicted in thin blue lines, enmities depicted in thick red lines.

1.3 Theoretical Framework

The empirical evidence on the Myanmar conflict shows that, although the Myanmar army faces a large number of enemies, it only attacks few of them in short time intervals (see Figure 1.1). In fact, forty out of the forty-seven armed groups in the sample are involved in at least one violent event with the Tatmadaw.[12] The purpose of the model is to describe how the heterogeneity stemming from the rich network structure among armed groups explains the Tatmadaw's decision to attack each group in a particular time frame.[13]

The model is divided into two parts: in the first part every armed group chooses its defensive capacity from a linear-quadratic function with externalities. The role of externalities is to keep track of alliances and enmities over time. In the second step, I assume that the Myanmar army knows the network structure so that it uses backward induction to reduce the overall defensive capacity of all armed groups in the network. Reducing the overall defensive capacity of all armed groups means to eliminate a group from the network. Since armed groups' defensive ability benefits positively from allies (and negatively from enemies) eliminating a group means to reduce its allies defensive capacity as well. Therefore, the model formalizes the "benefit" of removing an armed group from the network from the point of view of the Tatmadaw.

The framework draws on the contribution of Ballester et al. (2006) in which there are N agents that solve a static maximization problem. In what follows I will omit the subscript t because the problem below is solved in every period independently from what happened in the past (as well as what will occur in future periods). The envi-

[12]These groups are targeted either directly or through military activity causing casualties in their villages. Restricting the sample to events involving exclusively the Myanmar army and armed groups' militia confirms the results as shown in Table A.3 of the Appendix Section A.6.

[13]Powell (2012, 2013) shows that heterogeneity in rebels' characteristics drives the choice of a central government that decides to consolidate power peacefully or through violence. Indeed, rebels can differ along many observable (as well as unobservable) characteristics such as army size, alliances, enmities, territory and resources controlled.

ronment of the static game is as follows: in each period every armed group $i = 1, ..., n$ non-cooperatively chooses its *defensive capacity* $x_i \geq 0$ to maximize the following linear-quadratic payoff function:

$$U_i(x_1, ..., x_n) = \alpha x_i + \frac{1}{2}\rho x_i^2 + \sum_{j \neq i} \sigma_{i,j} x_i x_j. \tag{1.1}$$

Where α is a linear term set to be equal for every group.[14] $\rho < 0$ is a concavity parameter that prevents a group from expanding its defensive capacity indefinitely, it also has the intuitive interpretation that the larger a group's defensive capacity the easier is going to be detectable by the Tatmadaw (or other enemies). $\sigma_{i,j}$ captures bilateral influences across armed groups: the *sign* of $\sigma_{i,j}$ determines whether armed group i is allied with j ($\sigma_{i,j} > 0$, strategic complements) or an enemy ($\sigma_{i,j} < 0$, strategic substitutes). By the same logic, $\sigma_{i,j} = 0$ if i and j are neutral. In other words, the $\sigma_{i,j}$ keep track of the externalities deriving from alliances and enmities between groups.

Ballester et al. (2006) show that, under regularity conditions the above game has a Nash Equilibrium (their result is replicated in the Appendix Section A.1). Therefore, it is possible to "rank" armed groups according to their defensive capacity $x_i^\star(\Sigma)$ where Σ is the $x \times n$ matrix including the $\sigma_{i,j}$ of every armed group. The framework above is ideal to understand the incentives that the Myanmar army has in attacking a particular armed group. Since the equilibrium level of defensive capacity is embedded in the network structure of Σ, if the Tatmadaw knows the network structure it also knows what is the *defensive capacity* of each armed group. Importantly, this implies that the Tatmadaw can attack an armed group to reduce the overall defensive capacity in the network. "Removing" an armed group from the network has two effects: a direct one linked to the removal

[14]The model allows for a group specific α_i that can accommodate variation at the group level such as resource within the ethnic homeland, army size and population. However, it is much more transparent to control for these channels in the empirical analysis and let the model measure exclusively the value of alliances and enmities.

of the defensive capacity of group i ($x_i^\star(\Sigma)$) as well as an indirect one linked to the removal of the externalities on its allies and enemies $\sigma_{i,j}$. The intuition for the "indirect effect" is straightforward: removing a group from the network reduces its allies' defensive capacity as it reduces their ability to exchange goods or trade through the group's territories. The anecdotal evidence of such channel playing a role between armed groups in Myanmar abounds.[15]

The Tatmadaw's problem discussed above is formalized as follows:

$Max\{\sum_i x_i^\star(\Sigma) - \sum_i x_i^\star(\Sigma^{-\boldsymbol{i}}) \,|i = 1, ..., n\}$.

Ballester et al. (2006) show that this problem admits a solution that is linked to the contribution of each armed group to the *defesnive capacity* of other armed groups. The intercentrality parameter $c_i(\Sigma)$ (defined in the Appendix section A.1) captures each armed group contribution to others ' defensive capacity.

Theorem 1.1. *(This is Theorem 3 in (Ballester et al., 2006)). Under regularity conditions the key player i^* that solves $Max\ \{\sum_i x_i^\star(\Sigma) - \sum_i x_i^\star(\Sigma^{-\boldsymbol{i}}) \mid i = 1, ..., n\}$ is the one that has the highest intercentrality parameter within the network Σ.*

The theorem above sheds light on which armed groups are more likely to be attacked by the Myanmar army. In particular, it shows that a network statistic, the intercentrality parameter, carries information on the group's influence on other armed groups. Therefore, a reduced form interpretation of Theorem 1.1 is that armed groups with higher intercentrality parameter ($c_i(\Sigma)$) are more likely to be targeted. Anecdotal evidence discussed in section 1.2 shows that the Tatmadaw takes into account alliances and enmities in choosing whom to fight.

König et al. (2016) have recently stressed the role of the network of alliances and enmities during the Congolese civil war. The authors embed the framework of Ballester

[15] For example, (Lintner, 1999) and (Smith, 1999) document that the CPB was the main weapon supplier to the SSPP during the seventies and eighties. The same authors explain that the SUA was the main buyer of raw opium from smaller armed groups.

et al. (2006) together with a contest success function (Skaperdas (1996)) to show that each group fighting effort is affected by its alliances and enmities. Differently from their framework, this paper looks at the effect of alliances and enmities on the probability of being attacked by the Tatmadaw who acts as a rational planner that has full information about the network structure. Moreover, there is also a conceptual difference between the interpretation of alliances and enmities in the context of this paper and theirs. In the model of König et al. (2016), the fighting effort of an armed group is decreasing in the number of its first-degree allies and increasing in the number of its first-degree enemies. This is because armed groups compete for resources, therefore, the more allies the less competition for resources. By the same token, in their model, fighting increases the more enemies an armed group has. In this paper's framework, the defensive ability of a rebel group is an hypothetical measure of how dangerous that group is to the Myanmar army from a military perspective. Therefore, the defensive ability of an armed group is increasing in the number of its first-degree alliances and reduced in its first-degree enmities.

1.4 Data

The data is organized at geographical, temporal and armed group level. The unit of observation is a geographical cell (with side of length 16 miles) observed monthly from January 1989 to December 2015. In what follows, I describe the sources from which I gathered the data.

1.4.1 Armed Groups and Network Data for 1989-2015

Data on armed groups' alliances and enmities come from a variety of sources. The Myanmar conflict has been documented by several authors who covered different time frames. In this work I rely on the following sources to establish the relationships between the forty-seven armed groups in the sample: i) Lintner (1999, 1990) ii) Smith (1999), for coding alliances until the nineties, iii) South (2008) and iv) Oo and Min (2007) report alliances for the late nineties until 2006, v) the Myanmar Peace Center's website reports alliances and armed groups information with a focus on the period 2010-2015 vi) information from armed group's websites vii) Keenan (2013) reports alliances and enmities for the period 1989-2013, viii) International Crisis Groups and Euro Burma Office reports and other papers listed in the Appendix section A.2.

As these sources overlap, a direct comparison between them is possible. There are no conflicting records on whether groups are allied or enemies, i.e. it is never the case that two groups are reported to be allied in one source and enemies according to another one. However, sometimes information on small armed groups are only reported by some authors. Following the notation from the model $\sigma_{i,j}$ summarizes the information coming from the pairwise relationship between group i and j, this relationship is also referred as dyad in the rest of the paper. If no information about alliance (enmity) between armed groups is ever recorded at time $t = 1988$ the baseline coding for two groups is *neutrality* ($\sigma_{i,j} = 0$). In every period t, alliances (Enmities) are recorded symmetrically as $\sigma_{i,j} = 1$ ($\sigma_{i,j} = -1$).

The number of armed groups is stable over time with the exception of one group being disarmed in 1996 (SUA) and two groups entering the network in 1993 (ZRO) and 2010 (AAK). I constructed the network data at the month-year level starting from January 1988 until December 2015. The dataset has a total of 335,295 dyads, alliances make up a total of 16,612 dyads while there are 6,632 enmities recorded over time. Despite neutrality is the most common dyadic relationship, the network of armed groups is a giant component (i.e. there is no group that is isolated from the other armed groups). The network density varies over time from 0.05 and 0.11 so does its average degree that goes from a minimum of 2.53 to a maximum of 5.11. Variation in these measures is entirely driven by time variation in the network of alliances and enmities.

1.4.2 Rainfall Data

Following the influential contribution of Miguel et al. (2004) social scientists have studied the impact of rainfall (and weather shocks) on inter-group and inter-personal conflict. There is a general consensus that abnormal weather variation is associated with violence (see Burke et al. (2015) for a recent review). The sample of interest in this study is composed of rural areas in which subsistence agriculture is the norm. It is therefore important to measure the impact of weather fluctuations on conflict correctly so to purge estimates of the coefficient of interest from spurious correlations. Even though there are no comprehensive reports on the incidence of subsistence agriculture at the county level, NGOs' reports suggest that it is the prevalent activity in rural areas. Rice is the main subsistence crop that is grown in rebels' areas. Moreover, in areas whose elevation is too high for rice cultivation, rainfall affects soil moisture throughout the dry seasons which in turn impacts the yearly opium production. I am not the first to highlight the causal link between rainfall during the rain season and rice output and how this relationship affects conflict: Vanden Eynde (2016) shows that Maoist rebels in India are more likely to target Indian security forces whenever a negative rainfall shock hits a district in which the rebels' funding sources are not based exclusively on agricultural income.[16]

Rainfall data comes from two distinct sources. First, the Global Precipitation Climatology Centre (GPCC) (Schneider et al. (2011)) covers years before 2013 and has a spatial resolution of $0.5° \times 0.5°$ decimal degrees. Second, the Tropical Rainfall Measuring Mission (TRMM) from NASA which covers the period from 1998 onward, is based on satellite

[16]However, the author also highlights that this effect is reversed whenever agricultural income is the main source of funding of Maoist groups.The author argues that the reason for observing variation in the outcome of rainfall shocks on violence depends on the extent to which civilians in Maoist areas have an incentive to cooperate with Indian security forces.

images and has a finer resolution than the GPCC ($0.25° \times 0.25°$ decimal degrees). For additional details on limitations and advantages of each data source see the discussion in the Appendix section A.3.

1.4.3 Natural Resources and Price Data

Mapping the location of natural resources in Myanmar is hard because a lot of the mining activities occurs without licenses. For this paper, I rely on documents collected by the Extractive Industries Transparency Initiative (EITI). To date, this is the most complete source of information on the extractive sector in the country. The coding for mine presence is at the county level. Given the average size of a county in Myanmar, this choice is similar to Berman et al. (2015) coding of natural resources in Africa. Unfortunately, the EITI report lacks data on mine discovery. Therefore, there is no temporal variation in mine presence but only geographic variation in resources. However, temporal variation comes from the international prices of commodities available in Myanmar.[17]

1.4.4 Generating the Myanmar Grid

The geographical data is organized in cells of size $0.25° \times 0.25°$ decimal degrees, these are squares with side length of 27km (16mi) at the equator. The size of the cells has been chosen in order to associate armed group presence to each cell. This would have not been possible in the case of wider cells as the ethnic homelands of multiple groups intersect cells of size $0.5° \times 0.5°$. Cells have both cross-sectional as well as longitudinal differences. Cross-sectional variation includes cell's elevation, slope from the Global Agro-Ecological Zones' database. For every cell administrative unit classification such as county, district, state and bordering countries, are available from the Myanmar Information Management Unit. I also collected a cross-sectional measure of the land use (Land Use UNEP, source

[17] Additional details on how these were collected in the Appendix section A.5.

year 2000) to know if, within each cell, there are natural resources in the form of forests. Data on the transportation network in 2010 also comes from the Myanmar Information Management Unit. An alternative source (DIVA-GIS) reports roads within cells in 1993. Data discussed in the previous sections (1.4.1, 1.4.2, 1.4.3) are thus available at the cell level, providing time variation in rainfall, value of commodities, armed group presence and conflict events. Figure A.1 in the Appendix Section A.4 shows the cells within Myanmar. There are a total of 1139 cells within the country but only 600 of them are within territories affected by armed groups activity between the period of study. These 600 cells are enclosed within 153 counties (the smallest administrative unit available) and 47 districts. Every cell is observed monthly for twenty-seven years so that the dataset has nearly two hundred thousand cell-months observations. When using yearly data the sample has a little more than sixteen thousand observations.

1.4.5 Conflict Data

Data on conflict outbreaks during years 1989-2015 comes from different sources. The main source is the Georeferenced Event Dataset (GED) version 3.0 released by the Uppsala Conflict Data Program Croicu and Sundberg (2015). A few caveats of this database need to be discussed. The data is organized in dyads so that every event involves only two groups fighting each other. This data structure can be problematic if fighting activities in the country involve more than two groups. In order to assess whether this data structure introduces a systematic bias in observing fighting actors I compared the data from GED with a dataset collected by ACLED for the period 1996-2009 which has a total of 298 events and the advantage of reporting allies in conflict events.[18] Only in 2% of the cases (6 out of the 298 events) an armed group is reported to have an ally on the battlefield

[18] The 298 events only include clashes between armed groups or against civilians, the full dataset reporting riots and non-violent activities by armed groups has a total of 331 events.

which confirms that alliances are not primarily a means of sharing *directly* the burden of fighting on the same battlefield.[19]

More than 50% of the events in the GED database are recorded as violence against civilians. As explained in section 1.2, violence against civilians is an integral part of the Tatmadaw military strategy to fight rebels' groups. For this reason, I treat violence against civilians as directed to the rebel group that occupies the territory in which violence occurs. This choice does not change estimates' results nor their interpretation.

Every event in the GED data is coded at the monthly level, this allows the smallest time unit to be a month. Another advantage of this source is that it records where the event has occurred within Myanmar reporting the longitude and latitude of each event. This feature allows me to distinguish between violence against civilians that is unrelated to activity directed against a specific armed group such as the "Saffron revolution".[20]

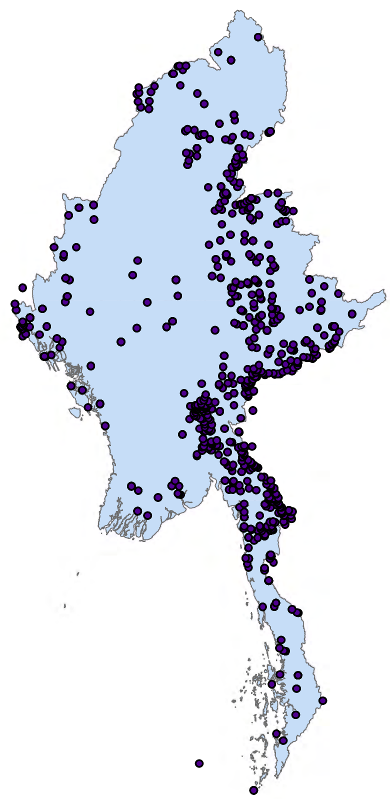
The second data source of conflict events comes from Myanmar newspapers' reports and covers the period from May 2013 to December 2015. The information included in these data is such that the GED data can be extended until 2015 as fighting sides, events' date and location are recorded. The two data sources are aggregated at the monthly and yearly level. Figure 1.5 shows the geographical distribution of the events from the two datasets. Once removing events unrelated to armed groups the sample consists of 2244 observations, there are a total of forty armed groups that are attacked at least once by the Tatmadaw. However, some groups are attacked more frequently than others, the KNU alone makes up for a third of the events in the sample. 40% of events (897) are classi-

[19] As discussed in sections 1.4.1 and 1.2 alliances are tied to mutual trading interests.

[20] From August to October 2008, Myanmar experienced a series of protests in its major cities that were violently suppressed by the Myanmar army and local police forces. However, it is well documented that armed groups played no role in staging or organizing these events. For this reason, in the empirical analysis I drop events coded as violence against civilians that do not occur within armed group's territories as they cannot be associated with violence targeted towards a specific armed group. Indeed, all events occurring in areas where the Tatmadaw has the monopoly of violence are related to police crackdown on protesters or clashes between Buddhists and Muslims. The unconditional probability of violence in these territory is indeed very low (0.2%) when compared with the one in armed groups' territories (1.16%).

fied as violence against civilians while the remainder are coded as violence between the Tatmadaw and a specific armed group. The dataset used in the empirical section aggregates, at the cell level, conflict data of Figure 1.5 as well as the rich cross-sectional and longitudinal characteristics described in sections 1.4.1, 1.4.2, 1.4.3, 1.4.4.

Figure 1.5: **Conflict Events in Myanmar 1989-2015**



Source: UCDP 3.0 GED and Myanmar Peace Center newspapers' report.

1.4.6 Parametrization and Model's Prediction

To obtain predictions from the model, I assign parameters and compute the intercentrality measure over time. The intercentrality of the N groups at time t is a non-linear function of the elements of equation 1.1, that is, $\sigma_{i,j,t}$ (network ties among the groups) as well as the model's parameter that do not change across groups and time: the linear parameter α and the concavity parameter ρ.[21]

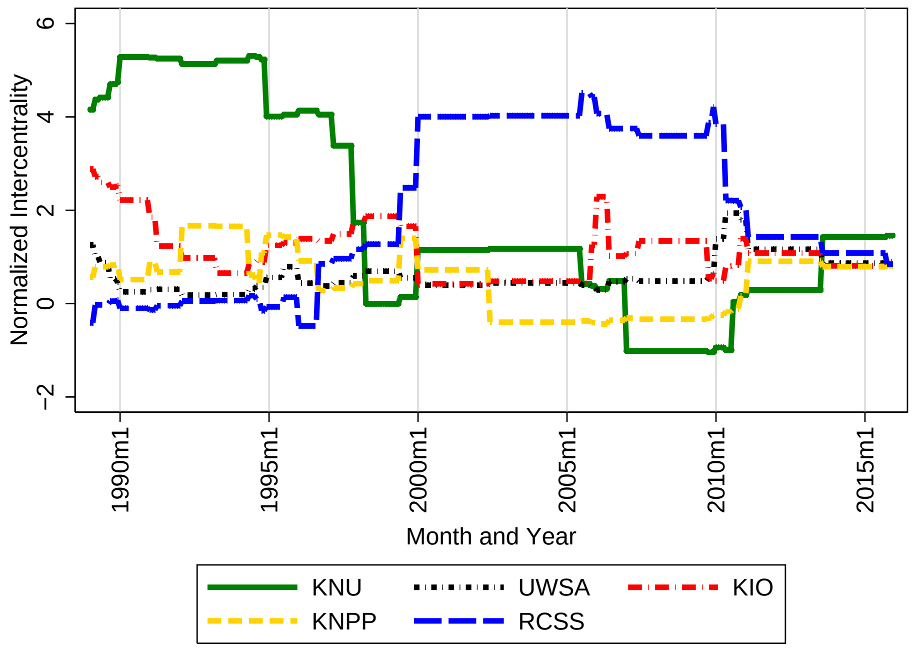
$\sigma_{i,j,t}$ comes from historical sources (as discussed in section 1.4.1). Figure 1.3 shows that the Myanmar army controls patches of territory virtually everywhere so that moving across different armed groups' territory become increasingly difficult as the distance from a group's homeland increases.[22] Since armed groups' presence is tied to their ethnic homeland, I weight inter-group relations by geographic distance. This choice scales down the value of alliances as the distance between groups increases and is based on the fact that groups far away from each other cannot trade or help each other on the battlefield. Every, $\sigma_{i,j,t}$ is divided by $\frac{1}{1+\sqrt{Dist_{i,j}}}$ where $Dist_{i,j}$ is the geodesic distance (in kilometers) between the areas under control of the armed groups. This choice is similar to Acemoglu et al. (2015) who estimate ties between historical Colombian municipalities using geographical distance adjusting for elevation change among them. To compute these values, I collect and depict maps of armed groups' presence over time (Figure 1.3 is an example for 1989).

Figure 1.6 shows how the intercentrality parameter changed from 1988 to 2015 for five of the forty-seven armed groups in the data. From the Figure, it is immediate to see that there is substantial heterogeneity in intercentrality at the group level. Indeed, while some groups rise and fall others remain stable over time.

[21]The intercentrality parameter can be flexibly adjusted to accommodate group specific characteristics through its linear parameter α_i.

[22]Historical evidence abounds with anecdotes of battalions being wiped out by the Tatmadaw while trying to reach areas controlled by allies (see (Lintner, 1999), (Smith, 1999)).

Figure 1.6: **Change in Normalized Intercentrality among five groups (1989-2015)**



1.5 Effect of Intercentrality on Conflict

1.5.1 OLS Results

In this section, I test predictions from the stylized model outlined in section 1.3. I use the rich cross-sectional and longitudinal variation in the data to identify the role of a group's intercentrality in explaining the fighting decisions of the Tatmadaw. Sub-section 1.5.1 explores alternative specifications to the one presented below. In sub-sections 1.5.2 and 1.5.3, I look at the impact of commodities shocks and exogenous rainfall fluctuations to show that the coefficient of interest is robust to the inclusion of other important determinants of civil war. Section 1.6 discusses the identification concerns which are addressed through an IV estimation. The dependent variable is a dummy for conflict measured at the cell-year level. Namely, for each cell c among territories controlled by armed group i in a given year t, $y_{i,c,t} = 1$ if conflict with at least one casualty is registered within the cell and zero otherwise.[23] While the model predicts which group is more likely to be targeted in light of its intercentrality, the empirical specification uses data for all armed groups' territories. Focusing on territories occupied by rebel groups allows to benchmark the mechanism of interest with respect to other determinants of conflict studied in the literature. In fact, armed groups' territories are exposed to commodities and weather shocks that are well known to cause conflict in the empirical literature. For instance, a cell controlled by group i with a gold mine can be attacked because in period t the international price of gold is high. By the same token, a weather shock can hit a portion of the territory hosting group i but not the other cells controlled by the same group. Throughout the paper, I also replicate the analysis using armed groups as units of observations showing that results are qualitatively unchanged. Equation 1.2 is the baseline specification estimated with a Linear Probability Model:

$$\begin{aligned} y_{i,c,t} &= \delta + \beta \text{ intercentrality}_{i,t} + \boldsymbol{\kappa} \text{ Geog.Controls}_c + \chi \text{Rain Season Drought}_{c,t} + \\ &+ \boldsymbol{\gamma} \text{Resources}_c + \boldsymbol{\psi} \text{ Resources' Prices}_t \times \text{Resources}_c \; + \boldsymbol{\rho y_{c,t-1}} \; + \theta_t + district_c + \epsilon_{i,c,t}. \end{aligned} \tag{1.2}$$

The baseline specification includes a vector of cell-level geographic controls (labeled Geog.Controls_c in the equation above) such as roads, average slope within the cell and a dummy if the cell is between the border with one of the neighboring countries. Equation 1.2 also controls for weather shocks in the form of a dummy called $\text{Rain Season Drought}_{c,t}$ taking value one if the cell experienced a drought during the last rain season. The variable called Resources_c is a vector of dummies for the presence of natural resources which I interact with a vector of international prices ($\text{Resources' Prices}_t \times \text{Resources}_c$). θ_t is a

[23]The sample excludes territories that are fully under control of the Tatmadaw in which political violence is unrelated to the ethnic armed groups. Indeed the main form of violence within areas under control of the Tatmadaw is violence against civilians which is not linked to any of the activities of armed groups in the border areas.

year fixed effect. A potential concern stemming from the stylized model is that it is static, that is, the Myanmar army chooses the group to attack given the intercentrality of each group at time t. However, the Tatmadaw observes groups rising and declining over time and might decide to attack a group according to the changes in its intercentrality rather than on its current level. First, if this mechanism is in place, then it goes against finding a significant effect on the β coefficient. For instance, if the Myanmar army attacks a group because it believes that its future intercentrality is going to increase, then $\hat{\beta}$ is going to be biased downward. Second, I control for the incidence of conflict within the cell during the previous year. In fact, $y_{c,t-1}$ in equation 1.2 denotes a dummy for conflict occurrence within cell c during the previous year. A district fixed effect controls for specific time-invariant unobservables at the geographic level. Because episodes of conquest of territories between armed groups are rare, the district fixed effect absorbs some of the variation of groups' intercentrality at the district level. For this reason, and because the prediction of the model uses the cross-sectional ranking among rebel groups, Equation 1.2 does not include an armed group fixed effect. In fact, according to the model, if an armed group's intercentrality is constantly above the one of other rebel groups, the group with the highest intercentrality is more likely to be attacked regardless of whether its intercentrality declined. For this reason, identification of the coefficient of interest relies on longitudinal and cross-sectional variation in armed groups' intercentrality. Since counties are the smallest administrative unit for which natural resources' data is available and their size is roughly equal across states, I cluster the standard errors at the county level (on average, a county has four cells).[24]

Coefficients estimated in Table 1.1 should be interpreted as expected unit change in the probability of conflict given a one unit standard deviation increase in the independent variable. For ease of interpretation, the intercentrality variable has been normalized. The

[24]Different choices of the cluster are explored in Section 1.6.1.

unconditional probability of conflict in the sample is 6.4% and a one unit standard deviation increase in a group's intercentrality increases the likelihood of conflict by 1.242% (column 1 of Table 1.1). In column (2), I add a lag that controls for conflict incidence within cell c during the last year, the size of the coefficient is slightly reduced but its significance does not change. In columns (3) to (5), I add the interaction between resources and their yearly prices (on the international market). Specifications in these columns show that positive shocks to the value of gold and teak have a much smaller impact on conflict than a group's intercentrality in explaining conflict.[25] All specifications in Table 1.1 control for the army size of each armed group i at time t. This control guarantees that the intercentrality parameter is not simply picking up the ability of a specific armed group of raising an army (omitting this control does not affect results). To summarize, Table 1.1 shows that the intercentrality coefficient is positively correlated with conflict; when including the full set of controls a one standard deviation increase in a group's intercentrality increases the probability of conflict by 1.2 percentage points over a baseline probability of conflict of 6.4%. Importantly, this effect is robust to the inclusion of natural resources' shocks and unexpected weather fluctuations thus identifying a distinct channel to explain conflict. Table A.5 in the Appendix Section A.6 shows more transparently how the result changes when adding one by one the commodities available in the country.

Alternative Specifications

The richness of the data allows for specifications that deviate from equation 1.2. As most data were collected at the month-year level, it is possible to run the specification at this finer time unit. Results are in Table A.1 in the Appendix Section A.6.[26] The precision and sign of the coefficient of interest does not change. When including the full set of controls,

[25] Myanmar has several natural resources: results for other commodities are in Table A.5 of the Appendix Section A.6.

[26] Equation A.3 is used to estimate the coefficients in Table A.1.

Table 1.1: **Linear Probability Model, Yearly Data**

Dependent Variable: Yearly Conflict Dummy

	(1)	(2)	(3)	(4)	(5)
Intercentrality	1.242***	1.224***	1.221***	1.234***	1.234***
	(2.903)	(3.236)	(3.228)	(3.268)	(3.239)
Rain Season Drought	0.259	0.246	0.235	0.249	0.231
	(1.216)	(1.267)	(1.231)	(1.273)	(1.205)
Army Size	-0.136	-0.154	-0.130	-0.096	-0.055
	(-0.234)	(-0.297)	(-0.255)	(-0.186)	(-0.106)
Roads in KM	2.288***	2.015***	2.019***	1.983***	1.974***
	(4.104)	(4.028)	(4.001)	(3.940)	(3.903)
Lag Conflict		4.315 ***	4.310***	4.310***	4.294***
		(10.673)	(10.653)	(10.611)	(10.581)
TeakPr. × TeakForest			0.471***		0.507***
			(3.009)		(3.283)
Gold Pr. × Mine				-0.181	-0.167
				(-0.808)	(-0.742)
# Observations	16940	16940	16940	16940	16940
# Clusters	153	153	153	153	153
Adj. R-Sq.	0.084	0.120	0.120	0.121	0.121
Year F.E.	Yes	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline probability of conflict in a year is 6.39%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: yearly data from Jan 1989 to Dec. 2015. Controls include Fixed Effects for District and Year, cell average slope, border dummy, interaction of international prices of commodities and dummies for their presence at the county level. Columns 2 to 5 include a dummy for lagged conflict within the cell in the previous year.
* p<.1, ** p< .05, *** p< .01

a one standard deviation increase in a group's intercentrality increases the probability of conflict by 0.09% over a baseline probability of conflict of 1.16%. The main differences resulting from varying the time unit of analysis is that the coefficient on the Rain Season Drought Dummy is now significantly different from zero while the coefficients on the interaction of commodities' prices and dummies for their presence are not. The latter result is likely caused by the fact that the effect of a price increase in a commodity takes time to result in increased violence.

The model presented in Section 1.3 delivers a prediction on which rebel group should be targeted in light of the network structure at time t. In Table 1.1, I take a reduced form approach to show that intercentrality is positively correlated with conflict potentially targeted towards many rebel groups. However, the data allow for a stricter test of the model's prediction over time. That is, I generate a dummy that takes value one when rebel group i has the highest intercentrality among all rebel groups in period t and zero otherwise. Therefore, I estimate equation 1.2 replacing $intercentrality_{i,t}$ with Intercentrality Dummy$_{i,t}$. Results are in Table A.2 and show that being the group with the highest intercentrality increases the probability of being targeted by three percent with respect to other rebel groups.

Table A.3 shows results when using armed groups observed monthly (yearly in columns (2-3)) as units of observations. That is, the dependent variable becomes $y_{i,t} = 1$ if group i is attacked in period t and zero otherwise. Doing so confirms that a group's intercentrality is positively correlated with the likelihood of being attacked by the Tatmadaw.[27] Note that the magnitude of the intercentrality coefficient in Tables A.3 (column (2)) and 1.1 (column (5)) is very similar: in both instances a one standard deviation increase of intercentrality is associated to a 20% increase of the probability of conflict over the yearly baseline probability.

In Table A.4, I drop events coded as violence against civilians in armed groups' territories. Hence, the coefficient of interest in Table A.4 is estimated exclusively using conflict between the Tatmadaw and ethnic armed groups. Doing so increases the precision with whom the coefficient of interest is estimated. Additional robustness checks in which I analyze how the precision of the estimates varies for different cluster definition in Section 1.6.1. The next section shows that the coefficient of interest is robust to the inclusion of different methods to measure the effect of commodities' shocks on conflict.

[27] In this specification I cluster the Standard Errors at the rebel group level showing robustness to alternative cluster definitions

1.5.2 Commodities and Conflict in Myanmar

Several seminal papers have shown the effect of natural resources on interstate and intra-state conflict.[28] In this study, I focus on a high spatial resolution data to measure the effect of commodities on conflict. Columns (3)-(5) in Tables A.1 and 1.1 show that some commodities have an impact on conflict. A criticism of this approach is that conflict need not be observed within the cell in which the commodity whose value suddenly increased is present. That is, conflict might spill over nearby cells, and the coding above is not capturing the true effect of shocks to commodities.[29] To address this concern, I build a measure of resources at the ethnic homeland level for each group. Namely, for each armed group I compute the variable $\textit{Ethnic Homeland Resource}_i = \sum_k Mine_k \mathbb{1}(\textit{Ethnic Homeland}_i)$ where $Mine_k$ is a dummy that equals one if commodity k is available in the groups' ethnic homeland. I normalized prices of commodities so that I could have a single price index capturing the effect of the overall market fluctuation at time t: $p_t = \sum_k p_{t,k}$, (with $p_{t,k}$ being the price of commodity k in t). Therefore, the interaction term is computed as the sum of interactions: $PriceIndex \times EthnicHomelandResources = \sum_k p_k \times Mine_k$. The equation to estimate becomes the following:

$$\begin{aligned} y_{i,c,t} = \; & \delta + \beta \text{ intercentrality}_{i,t} + \theta_t + \boldsymbol{\rho y_{c,t-1}} + \boldsymbol{\gamma} \text{ Ethnic Homeland Resources}_i + \\ & + \boldsymbol{\psi} \text{ Price Index}_t \times \text{Ethnic Homeland Resources}_i + \boldsymbol{\kappa} \text{ Geog.Controls}_c + \\ & + \chi \text{Rain Season Drought}_{c,t} + \text{district}_i + \epsilon_{i,c,t} \end{aligned} \tag{1.3}$$

Table 1.2 shows results of this exercise when using monthly (column (1)) and yearly (column (3)) data.[30] Controlling for group specific shocks does not change the signifi-

[28]Among them (Caselli et al., 2015), (Dube and Vargas, 2013), (Berman et al., 2015), (Michalopoulos and Papaioannou, 2016).

[29]Note that this concern is mitigated by the coding of resources' presence. Whenever a county has a resource, all cells within the county are coded to have that resource.

[30]The fixed effect θ_t picks up the effect of $PriceIndex_t$ which is omitted from equation 1.3.

cance of the coefficient estimating the effect of intercentrality on conflict. Columns (1) and (3) show that shocks to commodities are positively correlated with conflict, a one standard deviation increase in the interaction of prices and resources increases the probability of monthly (annual) conflict by 0.2 (2.4) percentage points. Results in Table 1.2 also show that the total resources in a group's homeland do not mechanically cause a group to be central as the coefficient on the variable *Ethnic Homeland Resources* is not significantly different from zero. Indeed, adding the variable measuring resources at the ethnic homeland does not change the significance nor the magnitude of the intercentrality coefficient in Table 1.2 when compared to Table A.1 and 1.1. This result is important as it shows that the positive correlation between intercentrality and conflict is not capturing a spurious correlation with a group's resources but identifying a channel that is salient for establishing which armed group the Myanmar army should attack. In columns (2) and (4) of Table 1.2, I interact a group's intercentrality with the shock that the group receives to the value of its resources. Since the intercentrality parameter has been normalized, it takes both positive and negative values. Hence, commodities shocks are (exogenous) "shifters" that should matter more to groups with higher intercentrality. Coefficients in columns (2) and (4) confirm this conjecture.

Table 1.2: **Commodities' Shocks to Intercentrality**

Estimates from Linear Probability Model

Dependent Variable:	Monthly Conflict Dummy		Yearly Conflict Dummy	
	(1)	(2)	(3)	(4)
Intercentrality	0.125***	0.149***	1.249***	1.206***
	(2.992)	(3.298)	(3.109)	(2.757)
Intercentr.× Pr.Index × EthnicHom.Res.		0.199***		1.002***
		(3.826)		(2.573)
Pr. Index × Ethnic Hom. Res.	0.193**		2.443***	
	(2.236)		(4.649)	
Ethnic Homeland Resources	0.090	0.098	0.971	1.181
	(1.032)	(1.089)	(1.129)	(1.323)
# Observations	195,641	195,641	16,940	16,940
# Clusters	153	153	153	153
Adj. R-Sq.	0.139	0.139	0.124	0.122
Month F.E. × Year F.E.	Yes	Yes	No	No
Year F.E.	No	No	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline probability of conflict in a year (month) is 6.39% (1.16%). T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: monthly data from Jan 1989 to Dec. 2015. in columns (1)-(2), Yearly data in (3)-(4). Controls in every regression include Fixed Effects for District, Indicator for below average rainfall during the previous rain season, cell average slope, border dummy. Columns (1) and (3) include six dummies for lagged conflict within the cell in the previous months. Columns (2) and (4) include a dummy for conflict within the cell in the previous year. * p<.1, ** p< .05, *** p< .01

1.5.3 Rainfall and Conflict in Myanmar

The goal of this section is to discuss how the variable measuring droughts during the rain season is constructed and to show that results are robust to alternative definitions of drought and sources measuring rainfall in Myanmar. The analysis in this subsection is performed at the month level as the $Rain\ Season\ Drought_{c,t}$ is not significant from zero t is a year.

I measure negative deviations from long-run cell averages with a dummy that equals one whenever the total rainfall in the rain season is in the lowest quartile of the distribution of historical rainfall within each cell during the rain season. I use this information to create the *Rain Season Drought* variable which takes value one from the end of the rain season until the beginning of the next rain season. I do this because rainfall shocks can have a delayed effect on conflict (something emphasized by Burke et al. (2015) in their review).

Table 1.3 shows estimates from a linear probability model with monthly data and the full set of controls in equation 1.2. What changes in this Table is the way the variable *Rain Season Drought* is constructed. Columns (1) and (3) look at abnormal deviations occurred throughout the full rain season span using the two distinct sources (TRMM and GPCC) of rainfall data. Using the TRMM data, the effect of a drought is positively correlated with conflict and significant at the 10% level, but this effect vanishes with the GPCC data. In columns (2) and (4) I focus on the last two months of the rain season: doing so shows that both sources capture a positive correlation between droughts and conflict. Note that the effect of a drought during the rain season is below eighty percent of the effect of a one standard deviation in a group's intercentrality.

The last column studies the presence of non-linear responses to weather shocks as found in previous studies in the literature (Hidalgo et al. (2010)). Simply, too much rain can also damage harvests causing negative income shocks to local population or armies relying on them for food and taxes. To show robustness of the intercentrality coefficient to non-linear responses of weather shocks, I construct a dummy called *Negative Rainfall Deviation* (*Positive Rainfall Deviation*) taking value one whenever the monthly deviation from average rainfall is 98% below (above) the long run monthly average. The inclusion of these events does not affect the intercentrality coefficient's significance. In conclusion, regardless of the source used, the coefficient of interest is not affected by deviation from average rainfall in the country.

Table 1.3: **Rainfall and Conflict**

Dependent Variable: Monthly Conflict Dummy.

	(1)	(2)	(3)	(4)	(5)
Intercentrality	0.095**	0.098**	0.095**	0.097**	0.095**
	(2.472)	(2.504)	(2.576)	(2.547)	(2.479)
Rain Season Drought (TRMM)	0.046*				
	(1.655)				
Rain Season Drought, last 2 months (TRMM)		0.076***			
		(2.991)			
Rain Season Drought (GPCC)			-0.046		
			(-0.747)		
Rain Season Drought, last 2 months (GPCC)				0.067**	
				(2.296)	
Negative Deviation					0.076**
					(2.272)
Positive Deviation					0.065**
					(2.404)
# Observations	195,641	195,641	195,641	195,641	195,641
# Clusters	153	153	153	153	153
Adj. R-Sq.	0.167	0.169	0.169	0.169	0.170
Month F.E. × Year F.E.	Yes	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline probability of conflict in a month is 1.16%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: monthly data from Jan 1989 to Dec. 2015. Controls include Fixed Effects for District, Month-Year, cell average slope, border dummy, six dummies for lagged conflict within the cell in the previous months interaction of international prices of commodities and dummies for their presence at the county level. * p<.1, ** p< .05, *** p< .01

1.6 Instrumental Variables Estimation

The evidence presented so far highlights a positive correlation between how connected a group is with other armed groups and the probability of being attacked by the Myanmar army. These results are robust to the inclusion of controls motivated by the literature studying civil wars. However, these results might still be affected by identification problems which I discuss below.

The intercentrality of a particular armed group can react to expected threats of conflict with the Tatmadaw. That is, some groups form alliances with each other because they expect to be attacked in the short term. While the literature on the civil war in Myanmar does not provide direct evidence on this issue, the concern of reverse causality between conflict and intercentrality is legitimate. Moreover, this criticism can work in the opposite direction: groups can break alliances to avoid conflict with the Tatmadaw. Therefore, alliances and conflict can be, at the same time, outcomes and explanatory variables of a simultaneous equation model. Failing to account for the true equation that determines the interplay of alliances and conflict causes an omitted variables bias in the estimates above. An additional concern is that the intercentrality variable is capturing a spurious correlation with conflict caused by time-varying unobservables at the armed group level. I address these concerns through an IV estimation.

The intercentrality parameter $c_{i,t}(\Sigma_{\mathbf{t}})$ is a non-linear function of the network structure described by the matrix $\Sigma_{\mathbf{t}}$. As the variable of interest is based on the endogenous network structure observed at time t, the first step for an instrumental variable is to predict a counterfactual network of alliances and enmities (i.e. $\widehat{\Sigma_{\mathbf{t}}}$). The counterfactual network is then used to compute the intercentrality parameter ($c_{i,t}(\widehat{\Sigma_{\mathbf{t}}})$) which is an instrument for the endogenous one (i.e. $c_{i,t}(\Sigma_{\mathbf{t}})$). Table 1.4 summarizes this procedure which I explain in greater detail below.

I estimate the parameters of a choice model of link formation to predict the pairwise

Table 1.4: **Summary of the IV Procedure**

1^{st} Step	Predict Counterfactual Network: $\widehat{\Sigma_{\mathbf{t}}}$.
2^{nd} Step	Compute Counterfactual Intercentrality: $c_{i,t}(\widehat{\Sigma_{\mathbf{t}}})$.
3^{rd} Step	Use $c_{i,t}(\widehat{\Sigma_{\mathbf{t}}})$ as an instrument for $c_{i,t}(\Sigma_{\mathbf{t}})$ in a 2SLS.

relationships, i.e. the $\widehat{\sigma}_{i,j,t}$, that are the entries of the adjacency matrix of alliances and enmities $\widehat{\Sigma_{\mathbf{t}}}$. In doing so, the variables entering the link formation model should not be systematically correlated with conflict happened in the recent past as this feature would violate the exclusion restriction. Namely, I estimate parameters of the empirical link formation model of equation (1.4) by maximum likelihood as a standard multinomial logit estimator. $U_{i,j,t}(\sigma)$ (where $\sigma \in \{-1,0,1\}$) is the dyad's joint utility from forming a positive (negative or neutral) link. This formulation assumes that utility is transferable across directly linked agents and that the observed connection is the one that maximizes the two groups' utility.[31]In doing so, I need to use variables that are not systematically correlated with conflict happened in the recent past as these would violate the exclusion restriction.

$$\begin{aligned} U_{i,j,t}(\sigma) = \; & FE_i + FE_j + \delta Ling.Dist_{i,j} + \beta Geog.Dist_{i,j} + \boldsymbol{\gamma}\, \boldsymbol{p}_t + \\ & + \boldsymbol{\kappa}\; CommonResources_{i,j} + \boldsymbol{\chi}\, \boldsymbol{p}_t\; CommonResources_{i,j} + u_{i,j,t}. \end{aligned} \tag{1.4}$$

The observable and unobservable components that affect the choice are discussed below:

[31] A limitation of this modeling choice is that it rules out interdependent link preferences. For example, consider three armed groups i, j and k, the decision of i and j to form an alliance is (assumed to be) independent from the potential alliance (or enmity) between i and k as well as j and k.I am not the first that uses this assumption to predict alliances between groups: Lai and Reiter (2000) use it to predict alliances between nations from 1816 until 1992.

1. FE_i , FE_j. The presence of groups' fixed effects is based on models of network formation that leave each group's degree heterogeneity unrestricted.[32] As shown by Graham (2015) for a link formation rule similar to the one above, omitting the groups' fixed effects from (1.4) causes the estimates for β, δ, γ , χ, κ to be biased. A standard feature of networks is that nodes vary in the general surplus they generate when forming a link. Therefore, including fixed effects also takes into account that some groups are better than others at establishing alliances (or enmities). For example, the RSO and NSCN-K only have one connection (i.e. degree one) with other armed groups but the KNU, RCSS and KNPP always have degrees that are above the average in the network.[33]

2. $Linguistic\ Distance_{i,j}$, $Geographic\ Distance_{i,j}$ are pre-determined pairwise variables that capture homophily stemming from observable characteristics, respectively, linguistic proximity between armed groups and geographic distance of groups i and j's ethnic homelands.[34] The inclusion of linguistic distance is justified on the grounds of the literature studying ethnicity and conflict. For instance, Spolaore and Wacziarg (2016) find that genetically similar populations are more likely to engage in inter-state conflict. Other authors Esteban et al. (2012) point out that ethnic polarization increases the risk of civil conflict. The coefficient on the distance between ethnic homelands measures how likely groups are to form a relationship as distance varies for reasons related to historical settlement choices of their ancestors.

3. $\kappa\ CommonResources_{i,j} + \gamma\ \boldsymbol{p}_t + \ \chi\ \boldsymbol{p}_t\ CommonResources_{i,j}$: these variables report the interactions between the monthly international prices of commodities at time t and

[32]See Graham (2014b) for an introduction to empirical models of network formation.

[33]This feature is common among all type of networks observed in nature (friends in school, trading partners, etc.) in which some nodes act as hubs while others have fewer connections.

[34]Linguistic distance is a measure of how close two languages are given their shared nodes in the linguistic tree. Desmet et al. (2012) introduced this measure.

a series of dummies ($CommonResources_{i,j}$) for the resources shared between groups. To be more specific, $CommonResources_{i,j}$ is a vector that includes a dummy for every resource that is shared by at least two different armed groups. The dummy equals one whenever groups i and j share a particular resource and zero otherwise. Their inclusion is motivated by the influential contribution of Caselli et al. (2015) who show that the presence of resources close to the border between two countries makes conflict between them more likely. Even though conflict between armed groups is rare in Myanmar, resources play an important role for groups' relationships. For example, South (2008) when commenting on a restored alliance between the KIO, RRF and NDA-K in 2005 writes that: "The formal reconciliation of KIO, RRF and NDA-K territorial disputes (...) seems to have been agreed primarily in order to facilitate logging activities in the rich forests of Northeast Kachin State rather than due to any great revival of fraternal spirit." Other anecdotes stress how opium growing groups have to rely on groups specializing in trading opium to sell and refine their opium harvests. I argue that the exogenous variation in the price of shared commodities drives the armed groups' incentives to meet and discuss how to share them (or how to smuggle across the border). Importantly, shared resources differ from the *Ethnic Homeland Resources* of Table 1.2, as these are only resources shared among ethnic groups and not representative of the overall resources within a group's ethnic homeland.[35] While the choice of using resources and exogenous variation in their prices to explain inter-group behavior over time seems to violate the exclusion restriction, I discuss how the particular IV design helps me to address this concern after presenting the estimates of the network formation model in Table 1.5.

[35]For instance, whenever a group has the "monopoly" over a certain resource this will not enter the *Common Resource* matrix.

4. $u_{i,j,t}$ are idiosyncratic components assumed to be i.i.d across dyads, the distributional assumption on them (type I extreme-value) ensures that we can write the conditional log-likelihood and estimate parameters through a multinomial logit specification.

Estimating equation (1.4) poses the well-known incidental parameter problem Neyman and Scott (1948): parameters' estimates are biased because of the estimation error generated by the fixed effects. Unfortunately, there is no formal result in the econometric theory that quantifies the bias deriving from estimating the above model.[36] Since the number of observations, $\frac{N(N-1)}{2}$, grows faster than the number of parameters to estimate, N, and the time series is very long (324 months), I choose not to correct for the (formally unknown) bias deriving from estimating fixed effects in a non-linear model.

[36] Graham (2015) solves a similar problem for a simpler Joint Maximum Likelihood as in his empirical model groups are either connected or not. To see how this problem differs from Hahn and Newey (2004), note that for each armed group I observe $N-1$ choices in every t. In fact, the number of fixed effects to estimate, N, is an order of magnitude smaller than the number of observations in the data as every period $\frac{N(N-1)}{2}$ observations constitute the sample size through which the F.E. is estimated.

Table 1.5: **Multinomial Logit Estimation of Network Parameters**

Dependent Variable is Monthly Dyad: $\sigma_{i,j,t}$				
	Enmity (1)	Alliance (2)	Observations 335295	Pseudo-R Squared 0.546
Linguistic Distance	0.267***	0.644***		
	(0.013)	(0.005)		
Ethnic Homeland Distance	0.973***	0.994***		
	(0.001)	(0.000)		
Weapon Trader	621.133***	0.954		
	(349.785)	(0.056)		
Opium Grower	64.194***	19.596***		
	(14.099)	(1.337)		
Opium Price	1.001***	1.001***		
	(0.000)	(0.000)		
Opium Grower × Opium Price	1.000**	0.998***		
	(0.000)	(0.000)		
Mine Gold	0.000***	0.151***		
	(0.000)	(0.022)		
Gold Price	1.001***	1.002***		
	(0.000)	(0.000)		
Mine gold × gold	0.999***	1.000*		
	(0.000)	(0.000)		
Mine copper	0.000***	0.000***		
	(0.000)	(0.000)		
Copper Price	1.000***	1.000***		
	(0.000)	(0.000)		
Mine copper × Copper	1.000***	1.001***		
	(0.000)	(0.000)		
Mine Silver	416.421***	82.843***		
	(214.819)	(12.409)		
Silver Price	1.015*	0.957***		
	(0.008)	(0.005)		
Mine Silver × silver	1.015	0.902***		
	(0.012)	(0.007)		
Teak Forest	0.052***	11.706***		
	(0.025)	(2.275)		
Teak Price	0.999***	0.999***		
	(0.000)	(0.000)		
Teak Forest × Teak Price	1.001*	0.998***		
	(0.000)	(0.000)		
Mine Lead	2.839***	0.733**		
	(0.706)	(0.091)		
Lead	1.000	1.000**		
	(0.000)	(0.000)		
Mine Lead × lead	1.000*	1.000***		
	(0.000)	(0.000)		
Mine Coal	1.217	0.802***		
	(0.196)	(0.057)		
Coal Price	0.993***	0.993***		
	(0.002)	(0.001)		
Mine Coal × Coal Price	0.990***	1.009***		
	(0.001)	(0.001)		
Mine Iron	3.804***	3.234***		
	(0.579)	(0.417)		
Iron	1.001	0.991***		
	(0.001)	(0.001)		
Mine Iron × Iron	1.007***	0.979***		
	(0.001)	(0.002)		
Mine Platinum	7.10e+07***	97.332***		
	(8.32e+07)	(23.207)		
Platinum Price	1.001***	1.000***		
	(0.000)	(0.000)		
Mine Platinum × Platinum Price	1.002***	0.999***		

Heteroskedastic-Robust S.E. in parentheses. * p<.1, ** p< .05, *** p< .01

Results from the multinomial logit estimation are in Table 1.5 in which Relative Risk Ratios are expressed over the base outcome (neutrality). For example, the relative risk ratio of being enemies over being neutral for a one-unit increase in *Linguistic Distance* between i and j is expected to decrease by a factor of 0.267 (holding the other variables fixed). This result implies that as Linguistic Distance increases between groups their likelihood of being enemies in the network decreases. Note that the interaction between $\boldsymbol{p}_t \times Common\ Resources_{i,j}$ are significant and help to explain what time variation generates alliances and enmities between groups. In Table A.5 (Appendix Section A.6), I show that most of these variables do not seem to have a direct effect on the probability of conflict between the Myanmar army and the rebel groups.

Table 1.6: **Non-Linear Effect of Alliance on the Intercentrality of some Groups**

7-2009	Rebel Groups and $\widehat{\sigma}_{i,j,t}$	KNPP $\leftrightharpoons$	KNU $\leftrightharpoons$	KIO	PSLF $\leftrightharpoons$	RCSS
7-2009	Predict. Intercen.: $c_{i,t}(\widehat{\boldsymbol{\Sigma}_\mathbf{t}})$	-0.53	2.41	0.71	0.34	1.65
8-2009	Rebel Groups and $\widehat{\sigma}_{i,j,t}$	KNPP $\leftrightharpoons$	KNU $\leftrightharpoons$	KIO $\leftrightharpoons$	PSLF $\leftrightharpoons$	RCSS
8-2009	Predict. Intercen.: $c_{i,t}(\widehat{\boldsymbol{\Sigma}_\mathbf{t}})$	-1.52 $\Downarrow$	2.45 $\Uparrow$	1.40 $\Uparrow$	1.52 $\Uparrow$	0.64 $\Downarrow$

Legend: $\leftrightharpoons$ denotes that $\widehat{\sigma_{i,j,t}} = 1$ between the groups connected by it.

Table 1.1 highlights that shocks increasing the international price of teak are positively correlated with the probability of an attack by the Myanmar army. Moreover, Table 1.5 shows that an (exogenous) increase in the price of teak negatively impacts the likelihood of an alliance being formed between groups sharing this resource. This result implies that, unless I can distinguish the impact of a price shock on conflict from its effect on the network formation between rebel groups, the exclusion restriction is unlikely to hold. To address this problem, I take advantage of the non-linear relationship between $\boldsymbol{\Sigma}_\mathbf{t}$ and the intercentrality variable. The non-linearity of $c_{i,t}(\boldsymbol{\Sigma}_\mathbf{t})$ stems from the fact that the change in a single alliance (or enmity) between two groups produces a non-linear variation in the intercentrality of all armed groups. The example in Table 1.6 illustrates this feature. Table 1.6 reports, for five armed groups in the sample, their pairwise relationships as predicted by the coefficients estimated with equation 1.4. Namely, the harpoon ($\leftrightharpoons$) between two groups means that they are (predicted to be) allied in July 2009, that is, $\widehat{\sigma}_{i,j,t} = 1$. Therefore, in July 2009 the KIO is allied with the KNU but not with the PSLF, which in turn is allied with the RCSS. Using the predicted network in July 2009 (i.e. $\widehat{\Sigma}_{\mathbf{July,2009}}$, I compute $c_{i,July,2009}(\widehat{\Sigma}_{\mathbf{July,2009}})$ for each group and report it below the rebel group's name.[37] In August 2009, the relationship between the KIO and PSLF is predicted to switch from neutrality to alliance while the other (predicted) relationships remain unchanged. The bottom row of Table 1.6 shows that the new alliance changed the predicted intercentrality of all groups in Table 1.6. For instance, while there is one degree of separation from the new link for the KNU and RCSS, the intercentrality of the former increased following the new alliance while the latter decreased. This non-linear effect allows me to control for the direct effect of a shock to the price of commodities (interacted with the dummy for the presence of the commodity) on conflict when I estimate the 2SLS. In other words, when estimating the Reduced Form model, I use the same specification of equation 1.2 and replace $c_{i,t}(\Sigma_t)$ with $c_{i,t}(\widehat{\Sigma}_{\mathbf{t}})$.

Table 1.7 reports results from the instrumental variable estimation when the baseline equation in column (5) of Table 1.1 is estimated through a 2SLS procedure. The coefficient on the IV is slightly larger than the OLS one: a one standard deviation increase in a group's intercentrality increases the expected probability that the Tatmadaw attacks a cell controlled by the group by 1.36 percentage points (as opposed to 1.23 in the OLS). The first stage diagnostics for the IV are shown in column (4): the correlation between the

[37]For simplicity, I am not showing the full network structure with forty-six active armed groups in these periods, but I use it to obtain the predicted intercentrality reported in Table 1.6. I choose the period between July and August 2009 because all the other predicted relationships are unchanged.

Table 1.7: **Instrumental Variable Estimation: Yearly Data**

Dependent Variable Yearly Conflict Dummy				
	OLS (1)	Red.Form (2)	2SLS (3)	First Stage (4)
Intercentrality	1.235***		1.364***	
	(3.239)		(3.068)	
Instrum. Intercentrality		1.195***		0.876***
		(3.154)		(13.745)
Adj. R-Sq.	0.121	0.120	0.121	0.532
F-test				188.931
Partial R-Sq.				0.35
# Observations	16940	16940	16940	16940
# Clusters	153	153	153	153
Year F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline conflict probability in a year is 6.39%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: yearly data from Jan 1989 to Dec. 2015. Controls include KM of Roads within the cell, altitude, dummy for drought during the last two months of the rain season, international prices of commodities as well as dummies for their presence at the county level. * p<.1, ** p< .05, *** p< .01

instrumented intercentrality and the "endogenous" one is high and precisely estimated as shown by the Partial R-squared (0.35) and F-test (188.93). Results with monthly data as well as using armed groups as units of observations are in Tables A.7 and A.8 (in the Appendix section A.7) and bolster the result obtained with yearly data.[38] An interpretation for why the IV coefficient is larger than the OLS one is that the Tatmadaw attacks groups before they achieve their "full" network potential in terms of allies. That is, armed groups are attacked when their influence on the network is rising but has not yet reached the highest intercentrality that each group can potentially achieve. Note that this pattern is consistent with a rational model explaining war as the outcome of shifting distribution of power between groups ((Fearon, 1995), (Powell, 2012)) as well as with models of pre-

[38]Estimates' precision in both monthly and yearly data is increased if events coded as violence against civilians are excluded from the sample (results available upon request).

ventive wars (Jackson and Morelli, 2011). Once the Tatmadaw realizes that the "power" of one group is growing rapidly (through alliances) war becomes the first-best choice to avoid the future shift in the power distribution.

Table 1.8: **IV Estimation without Fixed Effects to Predict the $\sigma_{i,j,t}$**

Dependent Variable Yearly Conflict Dummy

	OLS (1)	Red.Form (2)	2SLS (3)	First Stage (4)
Intercentrality	1.235***		4.632***	
	(3.239)		(4.745)	
Instrum. Intercentrality		1.794***		0.387***
		(4.066)		(6.742)
Adj. R-Sq.	0.121	0.122	0.088	0.309
F-test				45.4566
Partial R-Sq.				0.058
# Observations	16940	16940	16940	16940
# Clusters	153	153	153	153
Year F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline prob. of conflict in a year is 6.39%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: yearly data from Jan 1989 to Dec. 2015. Controls include KM of Roads within the cell, altitude, dummy for drought during the last two months of the rain season, international prices of commodities as well as dummies for their presence at the county level. * p<.1, ** p< .05, *** p< .01

A possible criticism of the IV procedure above is that groups' unobservable characteristics that might be spuriously correlated with intercentrality are loaded onto the fixed effects in equation 1.4 and used to obtain the predicted intercentrality. While omitting the fixed effects would bias the estimates of the remaining parameters of interest, (δ , β , γ , κ , χ) I address this problem excluding the fixed effects' coefficients when obtaining predictions for the $\widehat{\sigma}_{i,j,t}$. That is, I use the armed groups' fixed effects to estimate the remaining parameters of equation 1.4 but I omit their parameters' estimates when predicting $\sigma_{i,j,t}$. Doing so guarantees that the unobserved group-specific heterogeneity is exclusively used to correctly estimate the remaining parameters and not to predict the network structure.[39] Results from this exercise are shown in Table 1.8 (results for monthly data are in Table A.9 in Appendix Section A.7). As expected, the predicted intercentrality in the first stage explains the endogenous one less than when fixed effects are used in the predictions. However, the instrument is still positively and significantly correlated with the endogenous one (as shown by the F-test and the partial R-squared). The magnitude of the estimates increases with respect to results in Table 1.7 but overall this result is important as it shows that shared resources and their exogenous fluctuations over time are driving the variation in the network structure.

1.6.1 Additional Robustness Checks

An obvious concern for identification is that omitted variables, correlated with conflict and group' specific characteristics, are driving the spurious relation between intercentrality and conflict. If the adjusted R-squared does not increase as added controls are inserted in the specification, coefficient stability is not sufficient to show robustness of the estimated coefficient to omitted variable bias. Assuming that observable variables are related with unobservable ones, Oster (2016) proposes a test for coefficient stability. The author suggests an upper bound defined as R_{Max}, the hypothetical R-squared obtained if unobservables were available to the econometrician and added to the full set of controls, to be 1.3 times higher than the actual R-squared when all controls are added to the baseline specification. Fixing R_{Max}, the author computes the degree of proportionality between the (unobserved) covariance of the unobservables and the variable of interest vis-à-vis the (observed) covariance of the effect studied and the observable controls. The author defines this proportionality as δ and suggests that values of $\delta > 1$ should be viewed as robust. The larger δ, the greater the (hypothetical) effect of omitted variables should

[39] I thank Quoc-Anh Do, Horacio Larreguy and Nico Voigtländer for discussions and suggestions on this issue.

be in order for the observable effect of interest to be zero. The intuition is that unobservable variables should play a (proportionally) greater role than the observable ones in explaining the effect of interest.

Table 1.9: **Robustness to Unobservables using Oster (2016).**

Specification in the paper	R^2 with full set of controls	R_{max}	δ for $\beta = 0$
Table A.1 Col (5)	0.169	0.223	1.44
Table 1.1 Col (5)	0.121	0.168	5.837
Table A.3 Col (2)	0.318	0.43	1.38
Table A.4 Col (5)	0.14	0.19	3.866

The Table performs the robustness test discussed in Oster (2016). The first column has information of the specification on which the robustness test is performed. The second column reports the R-squared obtained with full controls, multiplying this number by 1.3 I obtain R_{max} in column 3. Finally, the last column reports the ratio of proportionality between the (hypothetical) covariance of unobservable variables with the variable of interest (intercentrality) and the covariance of the latter with observable variables. As suggested by Oster (2016), the effect of interest should be viewed as robust if the ratio is above 1.

Results are in Table 1.9 in which I perform the robustness test on several specifications presented in previous sections. For instance, for the specification with yearly data in Table 1.1 (column (5)), the unobservables would need to be 5.8 times more important than the observables in explaining conflict for the coefficient on intercentrality to be equal to zero. All of them display a coefficient of proportionality well above 1 which suggest that results estimated are robust.

An additional concern comes from the choice of the cluster when computing standard errors. In section 3.5 I argued that townships constitute the best cluster because townships have different resources that might drive specific patterns in conflict outbreaks. As suggested by Cameron and Miller (2015), I explore the sensitivity of results to different cluster definitions. I show how the standard errors change when choosing different clusters in Table 1.10. In columns (1) and (4) I use the PRIO-grids to cluster standard errors. PRIO-grids are cells of side 0.5×0.5 decimal degrees.[40,41] The advantage of using PRIO-

[40] The PRIO-grids are also the unit of observations of the GPCC rainfall data.

[41] An alternative specification that uses PRIO-grids Fixed Effects does not change results.

grids over townships is that their size is homogeneous and they are not subject to *ad-hoc* administrative definition from the Burmese authorities. In columns (2) and (5), I use districts (the administrative unit above townships) as clusters, this implies reducing the number of clusters by two-thirds. This estimation is meaningful if one believes that the District Fixed Effects are not capturing the full within cluster correlation. In columns (3) and (6), I compute standard errors taking into account serial and spatial auto-correlation following Conley (1999). More specifically, I use a spatial kernel of two thousand kilometers and a temporal lag structure of four years in both columns. Overall, Table 1.10 shows that estimates of the effect of interest are robust to alternative cluster definition.

Table 1.10: **Linear Probability Model: Different Clustering Choices**

Dependent Variable:	**Monthly Conflict Dummy**			**Yearly Conflict Dummy**		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercentrality	0.091**	0.091**	0.091***	1.234***	1.234***	1.234***
	(2.540)	(1.993)	(2.170)	(3.444)	(3.101)	(2.760)
# Observations	195,641	195,641	195,641	16,940	16,940	16,940
Cluster Type	PRIOgrid	District	Spatial HAC, 4yrs	PRIOgrid	District	Spatial HAC, 4yrs
# of Clusters	224	50	2000km	224	50	2000km
Month F.E. × Year F.E.	Yes	Yes	Yes	No	No	No
Year F.E.	No	No	No	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline probability of conflict in a year (month) is 6.39% (1.16%). T-statistic in parentheses from cluster robust S.E. with cluster level indicated in columns (1),(2),(4),(5). In columns (3) and (6), spatial and heteroscedasticity, auto-correlation consistent S.E. within 2000km and 4 years lags. Estimation period: monthly data from Jan 1989 to Dec. 2015 in columns (1)-(3), yearly data in columns (4)-(6). Controls include Fixed Effects for District, Month-Year, cell average slope, border dummy, interaction of international prices of commodities and dummies for their presence at the county level. Columns (1)-(3) include six dummies for lagged conflict within the cell in the previous months. Columns (4)-(6) include a dummy for conflict within the cell in the previous year. * p<.1, ** p< .05, *** p< .01

1.7 Conclusion

In this paper I study the determinants of conflict in Myanmar; in doing so, I contribute to the civil war and state formation literature. The main contribution to the civil war literature is to uncover a new mechanism that explains conflict outbreaks over time and space. The empirical literature studying civil wars analyzes their occurrence at the geographical level but often disregards actors because of the lack of data. In this study, I investigate the role of armed groups' alliances and enmities in shaping the Myanmar army's incentives to attack them. In particular, I show that alliances and enmities between armed groups generate variation in their *fighting ability*. Because of the complex web of inter-armed group's relationship, attacking a particular group weakens its allies (and makes its enemies stronger). I formalize this idea using a simple model that is applicable to several contexts not necessarily related to conflict. For instance, the model can explain governments' choices to attack different drug cartels or terrorist groups selectively. On a purely intuitive level, the model explains why Bashar al-Assad tolerated the "Islamic State"'s control of vast portions of Syria for so long and why the Islamic State might be able to survive even after it will lose most of its territories during the current offensive by the U.S. and Russia. As soon as the Islamic State will lose its influence in the region other armed groups will become the key enemies to fight from the perspective of the Syrian government.

I collected a new dataset on armed groups characteristics and their alliances for the period 1989-2015. Therefore, I obtain predictions from the model on which groups are more likely to be targeted as a function of their network structure I test predictions using geo-referenced and dyadic information for conflict events and actors in the last twenty-seven years finding strong evidence that the models' predictions explain the choices of the Myanmar army. These findings are robust to the inclusion of rainfall and commodity price shocks that affect the territory of armed groups unexpectedly. One of the main concerns when identifying the effect of alliances and enmities between armed groups on conflict is that of reverse causality. If past (or the expectation of) conflicts affects network formation the relation of interest cannot be correctly identified. To address this issue, I instrument the network structure using an econometric model of pairwise link formation. The econometric model is itself of interest because it sheds light on the role ethnicity and resources during civil wars. I find that the more similar the language spoken by ethnic groups, the more likely they are to be non-neutral to each other. This implies that similar groups are not necessarily more likely to join forces against the Myanmar army. The IV results confirm the findings of the OLS ones: alliances and enmities between armed groups help to predict which groups are going to be attacked by the Myanmar army.

The empirical evidence in the paper is consistent with theoretical findings pointing at war as the outcome of bargaining failures Fearon (1995), Powell (2006). Interpreting a group's intercentrality as a proxy for its bargaining power helps to explain why the Myanmar army cannot commit to peaceful deals with armed groups whose influence in the network is growing through new alliances. As the Myanmar army expects them to become stronger in the future, attacking influential groups is the optimal choice. Models of war as the outcome of bargaining failures are hard to test empirically because measuring the (ex-ante) probability that one side prevails on the battlefield is hard. Even though the intercentrality measure does not have a probabilistic interpretation, this work shows that its variation explains the Myanmar army's choice of monopolizing violence.

This paper is also of interest to scholars analyzing peaceful versus violent power consolidation in the process of state formation. Recent contributions on this topic displays mixed evidence. Acemoglu et al. (2013) analyze the case of Colombia and show that the central government prefers to come to terms with a rebel group (the AUC) so as to receive electoral supports in the areas where the rebel group's influence is greater. Another popular view is that civil conflict is the outcome of state formation (Tilly (1985)). In his recent theoretical contribution, Powell (2013) argues that both peaceful and violent power consolidation are optimal choices of a dynamic stochastic game in which the central government and a rebel group vie for control of the state. The author shows that the central government's choice to peacefully buying off the rebel group rather than fighting it depends on the individual characteristics of the rebel group such as the presence of resources in its homeland and its military strength. To shed light on how the process of state consolidation developed, I collected data on Myanmar's ceasefire agreements in the last thirty years. In the immediate future, I plan to study the Myanmar's army choices of peaceful and violent power consolidation during the last three decades. Finally, it will be important to explore how the variation in the use of force in Myanmar affected the current state perception and institutions in the ethnic armed groups' territories.

Appendices

Appendix A

Appendices

A.1 Model Appendix

I define the objects that characterize the equilibrium of the game in section 1.3. Throughout this section lowercase bold letters are used to denote vectors and uppercase bold letters denote matrices.

Consider the network $\mathbf{g}$ with adjacency matrix $\mathbf{G}$, let $\mathbf{M}(\mathbf{g}, \lambda/\beta) = [\mathbf{I_n} - (\lambda/\beta)\mathbf{G}]^{-1} = \sum_{k=0}^{+\infty} (\lambda/\beta)^k \mathbf{G}^k$, the parameter λ/β is a decay factor (that needs to be smaller than the inverse of the largest eigenvector of the adjacency matrix). The powers of the adjacency matrix keep track of the indirect connections in the network. $m_{ij} = \sum_{k=0}^{+\infty} (\lambda/\beta)^k g_{ij}^k$ counts the number of paths in the network $\mathbf{g}$ that start at i and end at j scaled by λ/β

Definition 1. *Bonacich Centrality Consider the network* $\mathbf{g}$ *with adjacency matrix* $\mathbf{G}$ *and a positive scalar* λ/β *s.t.* $\mathbf{M}(\mathbf{g}, \lambda/\beta) = [\mathbf{I_n} - (\lambda/\beta)\mathbf{G}]^{-1}$ *is well defined and nonnegative.*
The vector of Bonacich centralities in $\mathbf{g}$ *is* $\mathbf{b}(\mathbf{g}, \lambda/\beta) = [\mathbf{I_n} - (\lambda/\beta)\mathbf{G}]^{-1} \times \mathbf{1}$

Let the Bonacich Network centrality of node i be:
$b_i(\mathbf{g}, \lambda/\beta) = m_{ii}(\mathbf{g}, \lambda/\beta) + \sum_{j \neq i}^{n} m_{ij}(\mathbf{g}, \lambda/\beta)$ This is the sum of all paths starting from i.

Let Σ be the $n \times n$ matrix of cross effects, (Ballester et al., 2006) show that the above game can be rewritten as follows:

$$\Sigma = -\beta \mathbf{I_n} - \gamma \mathbf{U} + \lambda \mathbf{G}$$

Let $\underline{\sigma} = Min\{\sigma_{ij} | i \neq j\}$ and $\overline{\sigma} = Max\{\sigma_{ij} | i \neq j\}$, γ= -$Min\{\underline{\sigma}, 0\} \geq 0$, with $\beta = -\rho - \gamma > 0$ and $\lambda = \gamma + \overline{\sigma} > 0$. β measures the concavity of payoffs with respect to player i's x_i. Net Self-Substitutability $-\gamma\mathbf{U}$ is uniform across agents and captures global substituabilities. λ denotes the strength of local interactions and captures Local Complementarity. These transformations guarantee that $g_{ij} = (\sigma_{ij} + \gamma)/\lambda$ the entries of $\mathbf{G}$ are such that $0 \leq g_{ij} \leq 1$, i.e. the matrix $\mathbf{G}$ is well defined and nonnegative. With $\mu_1(\mathbf{G})$ I define the largest eigenvalue of the matrix $\mathbf{G}$

Theorem A.1. *(This is Theorem 1 in (Ballester et al., 2006)). Let the matrix of Bonacich centralities vectors* $[\beta \mathbf{I_n} - \lambda \mathbf{G}]^{-1}$ *be well defined and nonnegative* $\Leftrightarrow \beta \geq \lambda \mu_1(\mathbf{G})$*. Then the game* Σ *has a unique N.E. which is interior and is given by the vector* $\mathbf{x}^\star(\Sigma)$

$$\mathbf{x}^\star(\Sigma) = \frac{[\beta \mathbf{I_n} - \lambda \mathbf{G}]^{-1} \times \alpha}{\beta + \gamma \sum_i^n b(\mathbf{g}, \lambda/\beta)} \tag{A.1}$$

$$\frac{x_i^\star(\Sigma)}{\sum_i^n x_i^\star(\Sigma)} = \frac{b_i(\mathbf{g}, \lambda/\beta)}{\sum_i^n b(\mathbf{g}, \lambda/\beta)} \tag{A.2}$$

In particular each player's fighting potential is proportional to its centrality in the network so that more central groups have higher fighting potential in equilibrium.

Proof of Theorem A.1 : The proof is in the Appendix of (Ballester et al., 2006) (Proof of Theorem 1).

Definition 2. *Consider the network* $\mathbf{g}$ *with adjacency matrix* $\mathbf{G}$ *and a positive scalar* λ/β *s.t.* $\mathbf{M}(\mathbf{g},\lambda/\beta) = [\mathbf{I_n} - (\lambda/\beta)\mathbf{G}]^{-1}$ *is well defined and nonnegative. The intercentrality of player* i *of parameter* λ/β *in* $\mathbf{g}$ *is* $c_i(\mathbf{g},\lambda/\beta) = \dfrac{b_i(\mathbf{g},\lambda/\beta)^2}{m_{ii}(\mathbf{g},\lambda/\beta)}$

The Bonacich centrality of player i counts the number of paths in $\mathbf{g}$ that stem from i. The intercentrality parameter weighs the Bonacich centrality of armed group i by self loops. The Lemma below is useful to prove Theorem 1.1:

Lemma 1: let $\mathbf{M}(\mathbf{g},\lambda/\beta) = [\mathbf{I_n} - (\lambda/\beta)\mathbf{G}]^{-1}$ be well defined and nonnegative. Then $m_{ij}(\mathbf{g},\lambda/\beta) \times m_{ik}(\mathbf{g},\lambda/\beta) = m_{ii}(\mathbf{g},\lambda/\beta) \times \left[m_{jk}(\mathbf{g},\lambda/\beta) - m_{jk}(\mathbf{g^{-i}},\lambda/\beta)\right]$ for all $k \neq i \neq j$.

Proof of Theorem 1.1 : (The proof is in the Appendix of (Ballester et al., 2006) (Proof of Theorem 3)).

A.2 Network Data Appendix (Partially Incomplete)

Enmities do not necessarily imply that two groups are fighting each other at time t, most of the sources cited above describe groups as hostile even when there is no conflict between them during the period 1989-2015. For example, the KNLP and KNPP have been divided on ideology since the former joined the CPB alliance in the seventies. Similarly, allied groups do not necessarily fight side by side on the battlefield as they can be geographically far away from each other.[1] As explained in section 1.2, armed groups relationships are based on mutual economic interests rather than purely military ones. Therefore, two groups are considered allied not only if they fight together but also if any of the sources above records that the groups could freely move within each other' s territory. In other words, allies provide "safe harbors" as widely documented by historical evidence. For example, (Oo and Min, 2007) and (Smith, 1999) report that when

[1] I take this feature into account when I parametrize the model.

the Tatmadaw targeted the RCSS in the mid-nineties, they had a hard time finding them because the rebels were hiding within one if its ally's (the SSPP) territory. Similarly, in 1999 the RCSS reconquered an outpost on the Thai border by attacking the Tatmadaw through another of its ally's (the KNPP) territory. Once an alliance is coded at time t it stays unchanged until a source documents otherwise, that is, $\sigma_{i,j,t} = \sigma_{i,j,(t-1)}$ unless there is a source documenting that alliances have changed between t and $t-1$.

A.3 Rainfall Data Appendix

The GPCC database is assembled using gauge-based precipitation from stations within Myanmar. A potential concern that derives from using this source is that conflict might hinder rainfall measurement when it occurs in areas that are close to measuring stations. This problem is likely to be salient as several areas of Myanmar have been theaters of conflict since the fifties limiting the presence of measuring stations. To investigate deeper this concern, I obtained locations for rainfall stations that have more than ten years of data from the the Global Precipitation Climatology Centre (GPCC). Indeed, vast areas under control of ethnic armed groups do not have rainfall measuring stations. While this lack of data is partially addressed by rainfall stations in neighboring countries, there still are vast regions without records such as Central Shan and Kachin States. For this reason, I collect a second source of rainfall data: the Tropical Rainfall Measuring Mission (TRMM) from NASA. This source covers the period from 1998 onward, is based on satellite images and has a finer resolution than the GPCC ($0.25° \times 0.25°$ decimal degrees). Even though satellite measurements are not affected by conflict activity this source is not exempted from limitations.[2] This paper focuses on the period 1989-2015, hence, I use both sources as a proxy for rainfall as none of them covers the entire time frame of analysis. In fact, the

[2]The main drawbacks are discussed by (Romilly and Gebremichael, 2011)

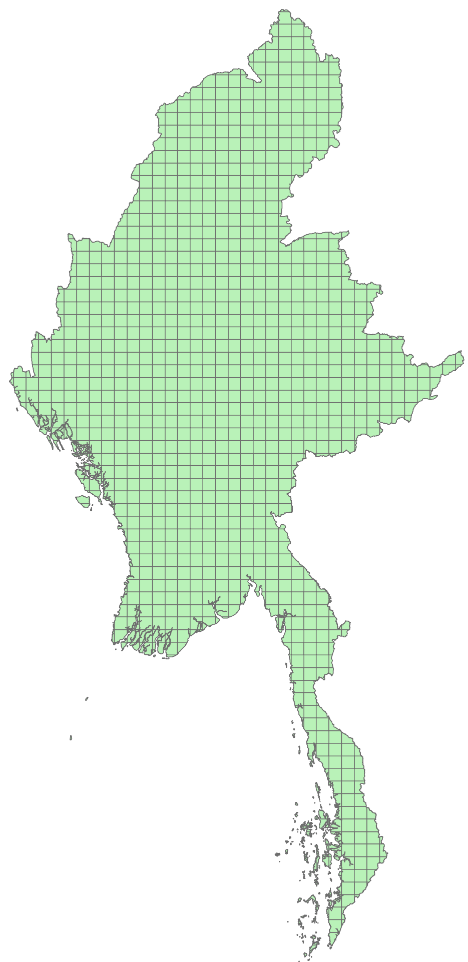
TRMM source is always used for the last three years and the GPCC are the only source that covers the period 1989-1998. In the empirical analysis I show that results do not change according to the source chosen.[3]

A.4 Conflict Data Appendix (Partially Incomplete)

Armed groups fighting each other *independently* from the central government, this feature is not common in Myanmar. In fact, the GED database reports 53 events (less than 3% of the total) in which two armed groups are fighting each other. Overall, three pairs of armed groups fight each other during the period of interest. However, Oo and Min (2007), Keenan (2013), Lintner (1999), Smith (1999), South (2008), all concur that the Tatmadaw is the mastermind behind every clash between armed groups. This claim finds additional evidence in the ACLED data, where there are no clashes between armed groups in which the Tatmadaw is not allied with one of the fighting groups. Therefore, I code clashes between armed groups as if they occurred between the Tatmadaw and the group against which the Tatmadaw and its ally fought.

[3] In most of Myanmar the rain season starts in June and peaks in August. Additional details on how rainfall data are used are in section 1.5.3.

Figure A.1: **Cells within the Myanmar Grid**



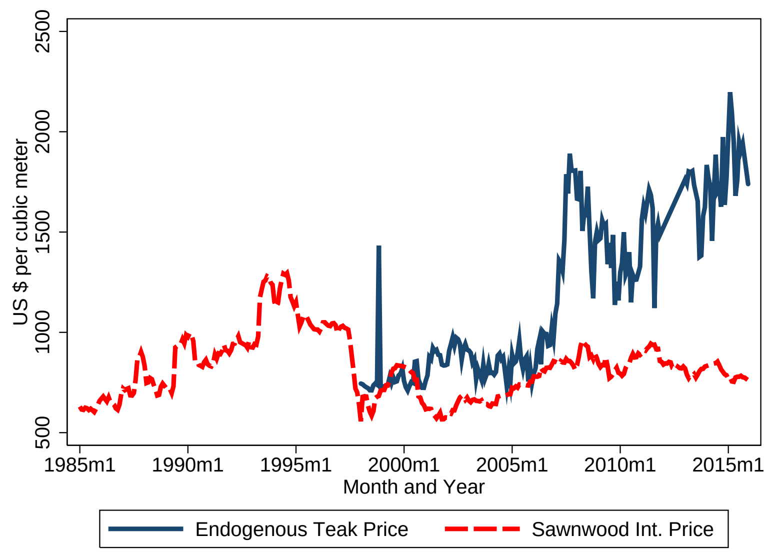
A.5 Commodities Appendix (Partially Incomplete)

International Prices of Commodities come from the World Bank *Global Economic Monitor (GEM) Commodities* database. Whenever prices for a particular commodity were not listed in this source, I used data from the United States Geological Survey Minerals Information webpage. The data collection effort faced the major challenge that some of the resources available in Myanmar are not extracted elsewhere (i.e. secular teak) or dominate the market price (i.e. jadeite). As local prices are clearly affected by conflict I use alternative sources as "instruments". For instance, I use the price of Malaysian Logs from the World Bank (GEM) database to approximate the price of teak. For precious stones such as rubies, sapphires and diamond, I used data collected by various websites reporting gemstones' prices.[4]

Instrumenting for the price of opium poses several challenges. First, Myanmar is among the top producers worldwide (UNODC, 2010). Second, Myanmar serves different markets than the leading producer (i.e. Afghanistan), this can be seen by the fact that shocks to Afghanistan's output have apparently no impact on Myanmar's prices (need to add graph in appendix). In summary, Afghanistan supplies its output to the European market while Myanmar serves the Asian and (to a minor extent) the US market. Since Colombian opium latex serves the U.S. market, I used these opium prices to instrument for Myanmar price. All commodities' prices were deflated using the U.S. CPI and expressed in 2010 US dollars.

[4]Additional details on how these issues were tackled are in the Appendix section A.5.

Figure A.2: **Endogenous Price of Teak vs. Intl. Price of Sawnwood**



Source: ITTO reports for Endogenous Teak Price and World Bank for Sawnwood Intl. Price.

A.6 Additional Robustness Checks

The monthly specification is estimated using the equation below:

$$y_{i,c,t} = \delta + \beta \text{ intercentrality}_{i,t} + \kappa \text{ Geog.Controls}_c + \chi \text{Rain Season Drought}_{c,t} + \\ + \gamma \text{ Resources}_c + \psi \text{ Resources' Prices}_t \times \text{Resources}_c + \boldsymbol{\rho y_{c,t-6}} + \theta_t + district_c + \epsilon_{i,c,t}. \tag{A.3}$$

Where t is now a month-year, that is, $y_{i,c,t} = 1$ if the Myanmar army caused at least one casualty in cell c controlled by armed group i during the month-year t. θ_t is a month-year fixed effect and $\boldsymbol{y_{c,t-6}}$ is a set of dummy for conflict occurred in $t-1$, $t-2$,..., $t-6$. Results in A.1 confirm the findings of 1.1

Table A.1: **Linear Probability Model, Monthly Data**

Dependent Variable: Monthly Conflict Dummy

	(1)	(2)	(3)	(4)	(5)
Intercentrality	0.178**	0.094**	0.094**	0.094**	0.098**
	(2.006)	(2.504)	(2.519)	(2.523)	(2.549)
Rain Season Drought	0.146***	0.076***	0.076***	0.077***	0.076***
	(2.894)	(2.991)	(3.008)	(3.004)	(2.991)
Army Size	-0.010	-0.019	-0.021	-0.016	-0.021
	(-0.086)	(-0.392)	(-0.423)	(-0.324)	(-0.431)
Roads in KM	0.205***	0.206***	0.206***	0.204***	0.205***
	(3.757)	(3.703)	(3.676)	(3.653)	(3.655)
Lag Conflict		2.315***	2.315***	2.315***	2.315***
		(14.670)	(14.670)	(14.670)	(14.666)
TeakPr. × TeakForest			0.007		0.008
			(0.521)		(0.543)
Gold Pr. × Mine				-0.030	-0.027
				(-1.034)	(-0.936)
# Observations	195,641	195,641	195,641	195,641	195,641
# Clusters	153	153	153	153	153
Adj. R-Sq.	0.026	0.169	0.169	0.169	0.169
Month F.E. × Year F.E.	Yes	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline probability of conflict in a month is 1.16%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: monthly data from Jan 1989 to Dec. 2015. Controls include Fixed Effects for District, Month-Year, cell average slope, border dummy, interaction of international prices of commodities and dummies for their presence at the county level. Columns 2 to 5 include six dummies for lagged conflict within the cell in the previous months. * p<.1, ** p< .05, *** p< .01

Table A.2: **LPM, Yearly Data: Dummy for Highest Intercentrality at time** T

Dependent Variable Yearly Conflict Dummy

	(1)	(2)	(3)	(4)	(5)
Intercentrality Dummy	3.099**	2.742**	2.765**	2.758**	2.762**
	(2.335)	(2.336)	(2.353)	(2.347)	(2.339)
Rain Season Drought	0.632	0.566	0.551	0.569	0.541
	(1.342)	(1.253)	(1.219)	(1.258)	(1.191)
Lag Conflict		23.110***	23.084***	23.084***	22.997***
		(10.671)	(10.651)	(10.611)	(10.574)
TeakPr. × TeakForest			1.482***		1.581***
			(3.097)		(3.356)
Gold Pr. × Mine				-0.468	-0.442
				(-0.826)	(-0.781)
Adj. R-Sq.	0.087	0.117	0.117	0.117	0.117
# Observations	16940	16940	16940	16940	16940
# Clusters	153	153	153	153	153
Year F.E.	Yes	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline probability of conflict in a year is 6.39%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: yearly data from Jan 1989 to Dec. 2015. Controls include Fixed Effects for District and Year, cell average slope, border dummy, interaction of international prices of commodities and dummies for their presence at the county level. Columns 2 to 5 include a dummy for lagged conflict within the cell in the previous year. * p<.1, ** p< .05, *** p< .01

Table A.3: **LPM Estimates with Armed Groups as Units of Observation**

Dependent Variable:	Monthly Confl. Dummy	Yearly Confl. Dummy	Yearly # Events
	(1)	(2)	(3)
Intercentrality	1.343***	5.237***	65.300***
	(4.670)	(3.667)	(4.549)
Rain Season Drought	0.105	-1.300	-4.078
	(1.031)	(-1.529)	(-0.839)
Roads in KM	-0.054	-1.221	1.840
	(-0.305)	(-0.644)	(0.309)
Lag Conflict	6.079***	14.159***	91.762***
	(9.924)	(5.831)	(3.038)
Army Size	0.207	4.653***	-7.846
	(0.521)	(3.601)	(-0.312)
Silver Pr.× Mine	0.196	2.476***	4.406
	(1.669)	(4.333)	(0.783)
Gold Pr. × Mine	-0.062	-0.725	0.092
	(-0.214)	(-0.498)	(0.006)
Nickel Pr. × Mine	-0.005	-0.470	-1.646
	(-0.022)	(-0.284)	(-0.310)
TeakPr. × TeakForest	-0.023	0.762	9.685
	(-0.235)	(1.018)	(1.410)
# Observations	14685	1224	1224
# Clusters	47	47	47
Adj. R-Sq.	0.407	0.295	0.383
Year F.E.	No	Yes	Yes
Month F.E. × Year F.E.	Yes	No	No

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. Unconditional probability of conflict with monthly data (column 1) is 7.2%. Unconditional probability of conflict with yearly data (column 2) is 24.5%. T-statistic from S.E. clustered at the armed group level in parentheses. Estimation period and sample: armed groups observed monthly from Jan 1989 to Dec. 2015 in column (1), armed groups observed yearly from 1989 to 2015 in column (2) and (3). Controls include Fixed Effects for Month and Year, six dummies for lagged conflict, armed group territories' average slope, dummies for resource presence at the armed group level. * p<.1, ** p< .05, *** p< .01

Table A.4: **LPM Estimates: excluding Conflict against Civilians**

Dependent Variable is Monthly Conflict Dummy					
	(1)	(2)	(3)	(4)	(5)
Intercentrality	0.193***	0.128***	0.126***	0.129***	0.122***
	(3.008)	(3.338)	(3.271)	(3.363)	(3.182)
Rain Season Drought	0.077*	0.025	0.026	0.026	0.026
	(1.868)	(0.943)	(0.960)	(0.976)	(0.968)
Roads in KM	0.127***	0.125**	0.122**	0.122**	0.123**
	(3.397)	(2.326)	(2.279)	(2.270)	(2.299)
Lag Conflict		1.510***	1.510***	1.509***	1.509***
		(9.126)	(9.128)	(9.131)	(9.131)
TeakPr. × TeakForest			-0.034**		-0.034*
			(-1.981)		(-1.924)
Gold Pr. × Mine				-0.074*	-0.072*
				(-1.938)	(-1.856)
Nickel Pr. × Mine					-0.023
					(-1.503)
Silver Pr.× Mine					0.006
					(0.200)
# Observations	195,641	195,641	195,641	195,641	195,641
# Clusters	153	153	153	153	153
Adj. R-Sq.	0.033	0.139	0.139	0.139	0.139
Month F.E. × Year F.E.	Yes	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline probability of conflict in a month is 1.16%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: monthly data from Jan 1989 to Dec. 2015. Controls include Fixed Effects for District, Month and Year, cell average slope, border dummy, international prices of commodities as well as dummies for their presence at the county level. Columns 2 to 5 include six dummies for lagged conflict within the cell in the previous months.
* p<.1, ** p< .05, *** p< .01

Table A.5: **LPM Estimates: Various Commodities**

Dependent Variable is Monthly Conflict Dummy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercentrality	0.096**	0.089**	0.091**	0.101***	0.088**	0.094**	0.098**
	(2.559)	(2.352)	(2.462)	(2.684)	(2.348)	(2.491)	(2.549)
Nickel Pr. × Mine	-0.025						-0.040**
	(-1.590)						(-2.551)
Silver Pr.× Mine		0.028					0.015
		(1.314)					(0.967)
Copper Pr. × Mine			0.030				0.024
			(1.350)				(1.231)
Iron Pr. × Mine				0.052*			0.057*
				(1.771)			(1.933)
Lead Pr. × Mine					0.022		-0.001
					(1.222)		(-0.077)
Platinum Pr. × Mine						0.040	0.113***
						(1.364)	(3.392)
# Observations	195,641	195,641	195,641	195,641	195,641	195,641	195,641
# Clusters	153	153	153	153	153	153	153
Adj. R-Sq.	0.169	0.169	0.169	0.169	0.169	0.169	0.169
Month F.E. × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline probability of conflict in a month is 1.16%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: monthly data from Jan 1989 to Dec. 2015. Controls include Fixed Effects for District, Month-Year, cell average slope, border dummy, six dummies for lagged conflict within the cell in the previous months, interactions of international prices of commodities and dummies for their presence at the county level. * p<.1, ** p< .05, *** p< .01

Table A.6: **LPM Estimates: Various Commodities**

Dependent Variable is Yearly Conflict Dummy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercentrality	1.254***	1.206***	1.207***	1.275***	1.200***	1.239***	1.235***
	(3.313)	(3.163)	(3.200)	(3.259)	(3.150)	(3.269)	(3.239)
Nickel Pr. × Mine	-0.238						-0.391***
	(-1.648)						(-2.775)
Silver Pr.× Mine		0.467**					0.404
		(2.512)					(1.575)
Copper Pr. × Mine			0.323*				0.120
			(1.920)				(0.845)
Iron Pr. × Mine				0.424*			0.451**
				(1.918)			(2.090)
Lead Pr. × Mine					0.351*		-0.025
					(1.936)		(-0.098)
Platinum Pr. × Mine						0.282*	0.837***
						(1.767)	(2.965)
# Observations	16940	16940	16940	16940	16940	16940	16940
# Clusters	153	153	153	153	153	153	153
Adj. R-Sq.	0.120	0.121	0.120	0.121	0.120	0.120	0.122
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline probability of conflict in a year is 6.39%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: yearly data from Jan 1989 to Dec. 2015. Controls include Fixed Effects for District, Year, cell average slope, border dummy, a dummy for lagged conflict within the cell in the previous year, interactions of international prices of commodities and dummies for their presence at the county level. * p<.1, ** p< .05, *** p< .01

A.7 Instrumental Variables: Additional Results

Table A.7: **Instrumental Variable Estimation**

Dependent Variable Monthly Conflict Dummy

	OLS (1)	Red.Form (2)	2SLS (3)	First Stage (4)
Intercentrality	0.091**		0.103**	
	(2.432)		(1.961)	
Instrum. Intercentrality		0.079**		0.768***
		(2.014)		(13.410)
# Observations	195,641	195,641	195,641	195,641
# Clusters	153	153	153	153
Adj. R-Sq.	0.169	0.169	0.169	0.482
F-test				179.8
Partial R-sq.				0.30
Year F.E. × Month F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable in columns (1)-(3), column (4) reports unstandardized regression coefficients. The baseline probability of conflict in a month is 1.16%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: monthly data from Jan 1989 to Dec. 2015. Controls include KM of Roads within the cell, altitude, dummy for drought during the last two months of the rain season, international prices of commodities as well as dummies for their presence at the county level. * p<.1, ** p< .05, *** p< .01.

Table A.8: **IV: Armed Groups as Units of Observation, Yearly Data**

Dependent Variable Yearly Conflict Dummy

	OLS (1)	Red.Form (2)	2SLS (3)	First Stage (4)
Intercentrality	5.237***		7.173**	
	(3.667)		(2.057)	
Instrum. Intercentrality		3.727*		0.519***
		(1.718)		(5.762)
Adj. R-Sq.	0.295	0.290	0.294	0.451
F-test				33.205
Partial R-sq.				0.2285
# Observations	1224	1224	1224	1224
# Clusters	47	47	47	47
Year F.E.	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable.Unconditional probability of conflict with yearly data is 24.5%. T-statistic from S.E. clustered at the armed group level in parentheses. Estimation period and sample: armed groups observed yearly from 1989 to 2015. Controls include Fixed Effects for Month and Year, six dummies for lagged conflict, armed group territories' average slope, dummies for resource presence at the armed group level interacted with the international price of resources. * p<.1, ** p< .05, *** p< .01

Table A.9: **IV Estimation without Fixed Effects to Predict the** $\sigma_{i,j,t}$

Dependent Variable Monthly Conflict Dummy

	OLS (1)	Red.Form (2)	2SLS (3)	First Stage (4)
Intercentrality	0.091**		0.736***	
	(2.432)		(4.889)	
Instrum. Intercentrality		0.237***		0.323***
		(4.529)		(5.941)
# Observations	195,641	195,641	195,641	195,641
# Clusters	153	153	153	153
Adj. R-Sq.	0.169	0.169	0.169	0.482
F-test				35.29
Partial R-sq.				0.04
Year F.E. × Month F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable in columns (1)-(2), column (3) reports unstandardized regression coefficients. The baseline probability of conflict in a month is 1.16%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: monthly data from Jan 1989 to Dec. 2015. Controls include KM of Roads within the cell, altitude, dummy for drought during the last two months of the rain season, international prices of commodities as well as dummies for their presence at the county level. * p<.1, ** p< .05, *** p< .01.

Chapter 2

Peaceful and Violent Power Consolidation: Evidence from Myanmar

2.1 Introduction

"For to win one hundred victories in one hundred battles is not the acme of skill. To subdue the enemy without fighting is the acme of skill." (Sun Tzu, *The Art of War*, Chapter 3).

A vast literature in economics and political science studies the determinants of civil conflict (Blattman and Miguel, 2010). That is, what are the conditions under which war is more likely to occur. While this literature has dramatically advanced the understanding of civil wars, it is still hard to explain the occurrence of war when peace is a viable alternative. For instance, why are some rebel groups continuously at war against a government while others receive peace deals and are absorbed into the political arena?[1]

To explain this puzzle, rational models of war provide a vast gamut of reasons. (Fearon, 1995) was the first to propose bargaining failures to explain why conflict might be preferable to a peaceful agreement. Since this seminal contribution, many authors have developed rational frameworks linked to bargaining failures. However, (Blattman and Miguel, 2010) underline how these frameworks have not been tested because of lack of data. This work analyzes the link between lack of commitment and conflict empirically; it does so focusing on Myanmar, the country hosting the longest civil war of our times. The advantages of studying this country are manifold. First, the duration and the multiplicity of rebel groups involved in it show patterns similar to many civil wars. For instance, some groups experience periods of persistent fighting while others reach negotiated settlements that occasionally fall apart reigniting conflict. Indeed, over the last sixty years the Myanmar government, in its various forms, faced more than forty armed groups and

[1] There are many examples of such instances in every civil war. In Colombia, the *Autodefensas Unidas de Colombia* (AUC) received a ceasefire deal at the end of the nineties and were disarmed between 2003 and 2006 Acemoglu et al. (2016). However, in the same period, the Colombian government did not reach an agreement with the other major group in the country, the *Fuerzas Armadas Revolucionarias de Colombia* (FARC) and continued to fight it. In Mali the *Coordination of Azawad Movements* (CMA) received a ceasefire deal in 2015 while the government has refused to come to term with other Islamist groups who represent a threat to the country' security.

occasionally reached ceasefires with many of them.[2] On the one hand, some of these ceasefires proved to be shortlived as conflict resumed. On the other hand, some groups are now no longer a threat to the Myanmar government as their troops coordinate movements with the government's army to avoid military confrontations.

I use the predictions of a formal model to explain the behavior of the Myanmar government. Namely, I use the stochastic game framework proposed by Powell (2013) in which the government chooses whether to consolidate its power peacefully (i.e. through ceasefire deals) or violently (i.e. through costly conflict). The government wishes to consolidate power to enjoy the resources within the contested areas in which a rebel group is active. Importantly, the government cannot commit to future transfers nor can the rebel group commit not to reignite conflict in the future periods of the game.[3] Crucially, the distribution of power between the two players is the state variable of the game. That is, the government can offer today's resources to the rebel group in exchange for a new distribution of power between the rebel group and the government itself. The goal of this offer, for the government, is to weaken the rebel group in the future by foregoing consumption of its resources today. Powell (2013) shows that this model admits three Markov Perfect Equilibria in pure strategies. In the first, when resources are large, the government and rebel group fight in either the first or the second stage of the game. If fighting does not erupt in the first period but further down the equilibrium path is because a ceasefire is optimal for both parties. A ceasefire allows both sides to fight on more favorable terms in future periods, that is, peacefully buying off the group for one period allows the government to fight a weaker enemy in the next period. In the third equilibrium, resources are sufficiently small so that the government eliminates the opposition

[2] In what follows, I use the word government as a catch-all category to refer to the military junta that ruled the country after 1988 until 2015.

[3] Lack of commitment is the driver of the bargaining failure in this model. There are other sources of bargaining failures that lead to conflict in rational models of war (see Jackson and Morelli (2011) for a review).

as quickly as possible (i.e. through consecutive offers of resources in exchange for a more favorable distribution of power until the rebel group is disarmed without fighting). I show that these three patterns describe well the empirical facts of the Myanmar civil war during the last twenty-seven years. To do so, I collected data on ceasefire agreements over time and rebel groups' characteristics to test the main predictions of the model. The preliminary empirical analysis shows that consolidation takes time as several periods occur before groups are fully disarmed. Moreover, positive shocks to natural resources as well as shocks to the defensive capacity of rebel groups are correlated with renewed fighting.

The rest of the paper is organized as follows. Section 2.2 lays down a model through which analyzing the choice of the government to peacefully assimilate a rebel group rather than fighting it on the battleground. Section 2.3 summarizes the history of the Myanmar civil war and shows anecdotal evidence confirming the findings of the model. Section 2.4 discusses the data used and shows empirical evidence that the Myanmar government follows the predictions of the model. Section 2.5 concludes.

2.2 The Model: Powell (2013)

The framework follows from (Powell, 2013), in this chapter I summarize the main results sticking to the notation in the original paper. The model consists of an infinite horizon stochastic bargaining game in which the government (G) and a rebel group (R) have to divide a pie that, in the context of Myanmar, stands for the per period payoff accruing from the resources in the rebel group's homeland. As long as both factions are armed the pie has size 1. Whenever one of the factions is disarmed the per period payoff increases to $1+\gamma$ (with $\gamma > 0$). The discount factor β is identical across groups so that $V \equiv \frac{1}{1-\beta}$ is the flow value of pies of size one. The timing is the following, at the beginning of period t, G makes a take-it-or-leave-it offer, ρ_t, which R can accept or reject. If R accepts the offer, G's proposal is implemented and the game moves to the next period $t+1$ in which

G makes a new proposal and so on. If R rejects the proposal, this causes fighting between the two players. The flow payoffs from fighting are, respectively, $f_G \geq 0$ and $f_R \geq 0$ with $f_G + f_R < 1$ (i.e. fighting is inefficient). Fighting presents two possible outcomes: a decisive military victory of one player or an inconclusive battle in which there are no winners and the game moves to the next round $t+1$.

$d_t \in [0,1]$ labels the probability of the game ending if R fights at t and $p_t \in [0,1]$ the conditional probability that R prevails given that t is the end period of the game. (Powell, 2013) defines the pair $s_t = (d_t, p_t)$ as the distribution of power at t.

G's offer ρ_t is a pair $\rho_t \equiv (z_t, \sigma_{t+1})$ with $z_t \in [0,1]$ being the share of the pie offered to R at time t. $\sigma_{t+1} = (d_{t+1}, p_{t+1}) \in [0,1]^2$ is the distribution of power proposed to which the game moves in $t+1$ if the offer is accepted. An inconclusive fighting results in $s_{t+1} = s_t$ with probability 1- ϵ, that is, the distribution of power stays the same in the following period. With probability $\epsilon \geq 0$ G's efforts to consolidate its power succeeds, that is, $s_t = \sigma_{t+1}$ in the next period.

In this framework, the author states the concept of "peaceful consolidation" in which $(E \equiv (d_t = 1, p_t = 0))$.[4] Therefore, G can eliminate R peacefully whenever R agrees to move to E.

The author restricts attention to Markov Perfect Equilibria (MPE) denoted by $\mathcal{E}$. A key assumption in this setup is that G can always induce fighting by making an offer that R rejects with certainty. For clarity, $V_j(s_k)$ is j's continuation payoff starting from s_k. This can be seen by writing the Peaceful Participation Constraint for R. At s_k, for R to accept G's proposal (z_k, s_{k+1}) it must be that:

$$z_k + \beta V_R(s_{k+1}) \geq f_R + \beta d_k p_k (1+\gamma) V + \beta(1-d_k)[(1-\epsilon)V_R(s_k) + \epsilon V_R(s_{k+1})]$$

With the Left Hand Side of the equation being the payoff from accepting the proposal

[4]That is, R is certain to lose in a military confrontation.

and the Right Hand Side being the payoff from fighting. Crucially, G's proposal affect the reservation value of R as long as $d_k < 1$ and $\epsilon > 0$.[5] Note that the offer $(z_t = 0, s_{k+1} = E)$ yields payoff of acecpting equal to βf_R while fighting yields $f_R + \beta d_k p_k(1+\gamma)V + \beta(1-d_k)[(1-\epsilon)V_R(s_k) + \epsilon f_R]$ with the latter being strictly larger.

Following this setup the author states three Propositions that describe the MPEs. Propositions 2.1 and 2.2 show that, as long as G has coercive power, it consolidates power by either buying off R or by monopolizing violence .

Proposition 2.1 (Coercive Power). *If G has coercive power at s_k and the factions do not fight at s_k in $\mathcal{E}$, then G consolidates power at s_k by weakening R as much as possible: If G can induce R to accept E at s_k, it does so at the minimal z_k satisfying the Peaceful Participation Constraint given s_{k+1}=E. Otherwise, G offers $z_k = 1$ in return for weakening R as much as possible by moving to an s_{k+1} that minimizes $V_R(s_{k+1})$ subject to the Peaceful Participation Constraint.*

Proof: see the Appendix in (Powell, 2013).

Proposition 2.2. *If G has coercive power at s_k and the factions fight at s_k in $\mathcal{E}$, then G names $s_{k+1} = E$ at s_k.*

Proof: see the Appendix in (Powell, 2013).

Proposition 2.3 describes the behavior of G when $\gamma > 0$. In particular, there are three different ways for G to consolidate power.

1. G fights at every period with R.

2. G peacefully buys off R as fast as possible.

3. G and R agree to a truce in period s_k but fight in s_{k+1}.

Fighting at s_k in equilibrium means that R prevails with probability d_k. Therefore, with probability $\epsilon(1-d_k)$ the next stage is $s_{k+1} = E$ so that the game ends. With probability

[5](Powell, 2013) calls this feature *Coercive Power* .

$(1-\epsilon)(1-d_k)$ there is a stalemate (i.e. the government's effort to shift the distribution of power to E is not successful) and the game remains at s_k. G offers E and fighting continues. The equilibrium payoffs to fighting at s_k are $F_G(s_k)$ and $F_R(s_k)$. $F_G(s_k)$ satisfies the recursive relation $F_G(s_k) = f_G + \beta d_k(1-p_k) + \beta(1-d_k)[(1-\epsilon)F_G(s_k) + \epsilon V_G(E)]$.[6] Rearranging terms yields:

$$F_G(s_k) = \frac{f_G + \beta d_k(1-p_k)(1+\gamma)V + \beta\epsilon(1-d_k)[(1+\gamma)V - f_R]}{1-\beta(1-d_k)(1-\epsilon)}.$$

For R the payoff of fighting at s_k is:

$$F_G(s_k) = \frac{f_R + \beta d_k p_k(1+\gamma)V + \beta\epsilon(1-d_k)f_R}{1-\beta(1-d_k)(1-\epsilon)}.$$

On the other hand, if R accepts G's offer then the payoff is the one of Proposition 2.1.

If G cannot fight in a single round it offers $z_k = 1$ and a s_{k+1} such that the Peaceful Participation Constraint binds. This yields $V_R(s_k) = 1 + \beta V_R(s_{k+1})$. So that we can substitute for $V_R(s_{k+1})$ in the Peaceful Participation Constraint:

$$V_R(s_k) = B(s_k) \equiv \frac{f_R + \beta d_k p_k(1+\gamma)V - \epsilon(1-d_k)}{1-\beta(1-d_k)(1-\epsilon) - \epsilon(1-d_k)}.$$

R payoff can be written as $V_R(s_k) = \Pi_R(s_k) \equiv max\{B(s_k), F_R(s_k)\}$ These two objects drive the decision of R to fight against the finish, whenever $B(s_k) > F_R(s_k)$ peaceful consolidation occurs as R's payoff of fighting to the finish is smaller than the transfer obtained on the equilibrium path.

The third possible continuation path is the one where fighting resumes at s_{k+n}. While this equilibrium might seem counter-intuitive, it fits the case of several civil conflicts and particularly the Myanmar one. The Kachin Independence Organization, for instance, signed a ceasefire in 1994 that lasted for seventeen years before fighting resumed in 2011. In fact, most armed groups in Myanmar signed ceasefires with the government. However, fighting between rebel groups and the Myanmar government resumed. The model provides a formalization of this empirical fact. There are two reasons for why G is not willing to fight at s_k: G might prefer to fight in a later period when fight is more

[6] $V_G(E) = (1+\gamma)V - f_R$.

decisive (i.e. less costly) and it has higher level of coercive power over R. That is, G offers $(1, \tilde{s}_{k+1})$ and then fights at $\tilde{s}_{k+1}$. $\tilde{s}_{k+1}$ is such that the Peaceful Participation Constraint binds minimizing $z_k + \beta V_R(s_{k+1})$. By Proposition 2.1, R acceptance of the offer implies that $V_R(s_k) = \Pi_R(s_k)$ and $V_G(s_k) = \beta F_G(\tilde{s}_{k+1})$ with $\tilde{s}_{k+1} = (1, \tilde{p}_{k+1})$ and $\tilde{p}_{k+1}$ is determined by $\Pi_R(s_k) = 1 + \beta V_R(\tilde{s}_{k+1}) = 1 + \beta F_R(\tilde{s}_{k+1}) = 1 + \beta[f_R + \beta \tilde{p}_{k+1}(1+\gamma)V]$.

Given the continuation payoffs defined above, $\Pi_G(s_k), F_G(s_k)$, and $\beta F(\tilde{s}_{k+1})$, G monopolizes violence according to $max\{\Pi_G(s_k), F_G(s_k), \beta F(\tilde{s}_{k+1})\}$.

Proposition 2.3 (Monopolizing Violence). *G monopolizes violence when $\gamma > 0$. How G monopolizes violence depends by $max\{\Pi_G(s_k), F_G(s_k), \beta F(\tilde{s}_{k+1})\}$:*

- *If $F_G(s_k) > max\{\Pi_G(s_k), \beta F_G(\tilde{s}_{k+1})\}$ G fights at s_k, with $s_{k+1} = E$, $V_R(s_k) = F_R(s_k)$ and $V_G(s_k) = F_G(s_k)$.*
- *If $\beta F_G(\tilde{s}_{k+1}) > max\{\Pi_G(s_k), F_G(s_k)\}$, G and R fight at $\tilde{s}_{k+1}$ with $V_R(s_k) = \Pi_R(s_k)$ and $V_G(s_k) = \beta F_G(\tilde{s}_{k+1})$.*
- *If $\Pi_G(s_k) > max\{F_G(s_k), \beta F_G(\tilde{s}_{k+1})\}$, G induces R to agree to E as fast as it is peacefully possible with $V_R(s_k) = \Pi_R(s_k)$ and $V_G(s_k) = \Pi_G(s_k)$.*

Proof: see the Appendix in (Powell, 2013).

2.2.1 Comparative Statics

The following sub-section shows that the decision of consolidating power peacefully rather than violently depends on γ and the initial distribution of power. Propositions 2.4 and 2.5 state these concepts and drive the empirical analysis of Section 2.4. Proposition 2.4 explain the relationship between γ (the resources in R's ethnic homeland) and the decision of G to monopolize violence. Resources create a trade-off in the model. Peaceful consolidation avoids the deadweight loss linked to conflict but takes time as G might have to wait several periods before R is weakened. This delay is a cost for G, the larger γ, the greater the cost for G. The Proposition below formalizes this concept:

Proposition 2.4. *There exist thresholds $0 < \underline{\gamma} \leq \bar{\gamma}$ such that G eliminates R as quickly as is peacefully possible when $0 < \gamma < \underline{\gamma}$ and fights at either s_k or $\tilde{s}_{k+1}$ when $\gamma > \bar{\gamma}$.*

Proof: see the Appendix in (Powell, 2013).

Similarly f_G and f_R play a role in the likelihood of observing violence versus peaceful consolidation. A lower opportunity cost of fighting (i.e. the higher f_G or f_R) makes conflict more likely.

Finally, one is interested in the effect of p_k (a measure of R's military strength) on the conflict's choice. The stronger R the more likely are factions to fight. An increase in p_k decreases both the payoffs from fighting and consolidating power through peace for G. However, the difference between $F_G(s_k) - \Pi_G(s_k)$ and $\beta F_G(\tilde{s}_{k+1}) - \Pi_G(s_k)$ increases. This means that the government is more likely to buy off weaker groups.

Proposition 2.5. *If the contingent spoils are sufficiently large, fighting becomes more likely as the flow payoffs during periods of fighting f_G or f_R increase or the opposition becomes stronger (i.e. p_k increases).*

Proof: see the Appendix in (Powell, 2013).

The following section explains the approach used to measure the strength of each rebel group active in Myanmar.

2.2.2 Defining the Rebel Group's Military Strength

The framework presented in the sections above shows that the military strength is a crucial parameter to explain the strategy of consolidating power. Given the variety of armed groups active in Myanmar between 1988 and 2015, an empirical test of the model requires mapping p_k for every group i in the country. To do so, I use the framework of

(Ballester et al., 2006) that uses heterogeneity in the network structure as a driver of the different *defensive capacity* of each armed group. See the model in Section 1.3 for additional details. In what follows I use the defensive capacity as defined by A.1 in the Appendix Section A.1. Of course, the *defensive capacity* of each group does not have a probabilistic interpretation but it serves as an approximation for an otherwise unobservable set of parameters.

2.3 Historical Background

A brief summary of the Myanmar civil war is in Section 1.2. This section focuses on providing examples and anecdotes to understand how the Myanmar government pursued a ceasefire politics starting from the late eighties. The choice of focusing on the period starting in 1989 is two-fold. First, an internal coup changed the leadership within the Myanmar army, that is, from 1989 until 2011 Than Shwe, was the head of the military as well as the most powerful person in the country. Second, multiple sources cover this time frame making data on ceasefires verifiable, until our days.[7]

Following the internal coup that changed the ruling leadership within the Myanmar army, the generals changed their strategy with rebel groups. In particular, multiple sources saw the implosion of the Communist Party of Burma (CPB) as an opportunity to come to terms with some groups and suspend fighting. In fact, starting from 1989 at least forty groups signed a ceasefire with the Myanmar government. Ceasefires' terms vary from group to group and they are best described as negative peace. That is, the government and rebel group agreed not to fight each other (and occasionally demarcate each other's territory) but kept their weapons and no political concessions were made.[8] Over time, the government offered to some groups that enjoyed long-lasting deals, to transition

[7]The data in this chapter start in January 1988 until the beginning of October 2015.

[8]See Buchanan (2016), Callahan (2007) and Oo and Min (2007) for a description of the ceasefires.

into the schemes called *Border Guard Force* (BGF) or *People Militia'* (PM). These agreements are such that the Myanmar army exerts a greater oversight on the rebel groups' activities. For instance, groups that agree to join the BGF scheme agree to have members of the Myanmar army within their battalions. Of course, not every armed group accepts the transition from ceasefire group to BGF. For instance, the DKBA5, a group that signed a ceasefire in 1995 with the government, refused such an agreement in 2010. In one case, the Pa-O National Organization (PNO), a similar agreement paved the way for a transition into a political party that presented candidates in both local and national elections. While these features are common to several civil wars, in the next section I show how the data collected explain the choice of the Myanmar government to peacefully assimilate some groups following the predictions of the model in Section 2.2.

Table 2.1: **Rebel Groups between 1989 and 2015**

Group's Acronym	Ever Signed Ceasefire before October 2015?	Ceasefire Unraveled?	Active in 2015?	Transitioned into BGF or PM
AA	No		Yes	No
ABSDF	No		Yes	No
CNF	No		Yes	No
DKBA	Yes	No	Yes	Yes
DKBA5	Yes	Yes	Yes	No
God's Army	Yes	Yes	No	Yes
KDA	Yes	No	Yes	Yes
KIO	Yes	Yes	Yes	No
KNDPA	Yes	No	Yes	Yes
KNG	Yes	No	Yes	Yes
KNLAPC	Yes	Yes	Yes	No
KNLP	Yes	No	Yes	Yes
KNDP-H	Yes	Yes	Yes	Yes
KNPP	Yes	Yes	Yes	No
KNSO	Yes	No	Yes	Yes
KNU	Yes	Yes	Yes	No
KPC	Yes	No	Yes	No
KSNLF	Yes	No	Yes	Yes
MAMD	Yes	No	Yes	Yes
ManPanMG	Yes	No	Yes	Yes
MNDA	No		Yes	No
MNDAA	Yes	Yes	Yes	No
MNDAABf	Yes	No	Yes	Yes
NayaiG	Yes	No	Yes	Yes
NDAAESS	Yes	No	Yes	No
NDA-K	Yes	No	Yes	Yes
NMSP	Yes	No	Yes	No
NNSC	No		Yes	No
NUFA	No		Yes	No
PadohAS	Yes	No	Yes	Yes
PNLO	No		Yes	No
PNO	Yes	No	No	Yes
PSLP	Yes	Yes	Yes	No
RCSS	Yes	Yes	Yes	No
RRF	Yes	No	Yes	Yes
RSO	No		Yes	No
ShwepyA	Yes	No	Yes	Yes
SSAN3	Yes	Yes	Yes	Yes
SSAN7	Yes	Yes	Yes	Yes
SSA-S758	Yes	No	Yes	Yes
SSNA	Yes	Yes	Yes	No
SSNLO	Yes	Yes	Yes	No
SSPP	Yes	Yes	No	No
SUA	Yes	No	No	No
T-KN	Yes	No	Yes	Yes
UWSA	Yes	Yes	Yes	No
WNO	No		No	No
ZRO	No		Yes	No

See Section 2.3 for Sources. Ceasefire Unraveled implies that the armed group clashed with the Myanmar government after signing the ceasefire. Active in 2015 in 2015 labels whether the group has still access to weapons. Transitioned into BGF or PM indicates whether the group has agreed to transition into a People Militia Force or Border Guard Force (see Section 2.3).

2.4 Empirical Evidence

2.4.1 Data

To test the predictions from Powell (2013), I collected a rich dataset which I briefly describe in this Section. For each rebel group, I gathered information on ceasefire deals signed in the last thirty years between the Myanmar government and the various armed groups active in the country. In particular, this information reports in which month and year the Myanmar government breaks a deal with a particular rebel group. Pairing this information with the ones on conflict outbreaks over time (see Section 1.4.5), I observe when the government is monopolizing violence against a particular group. That is, I observe when ceasefires deals fall apart, and the Myanmar government chooses to monopolize violence. Since groups are observed over time, I know when a particular group disarms. Table 2.1 includes information of whether a group ever signed a ceasefire deals with the government and whether this deal fell apart (i.e. the parties fought at some point after signing the ceasefire). The third column includes information on whether the group has been completely disarmed or not by October 2015. The last column displays whether the group agreed to transition into a BGF or PM scheme. These schemes imply a very high level of coordination with the government that is in line with a distribution of power more favorable to the Myanmar government. Overall, Table 2.1 shows that most armed groups sign ceasefire deals but for some of them these are short-lived. The armed group level variation displayed in Table 2.1 is important to test the theoretical predictions as only some groups are assimilated through long lasting peaceful deals while others are facing the government on the battleground (see Chapter 1).

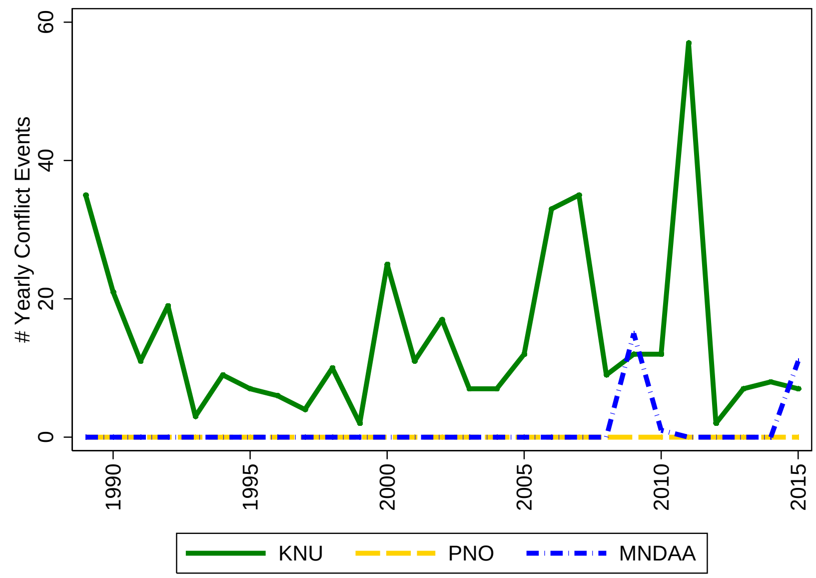
I also collected data on the presence of natural resources within the ethnic homelands as well as the territories controlled by each armed group over time (see Section 1.4.3). For each armed group, I compute the variable $\textit{Resources in Ethnic Homeland}_i$ =

$\sum_k Mine_k \mathbb{1}(\textit{Ethnic Homeland}_i)$ where $Mine_k$ is a dummy that equals one if commodity k is available in the groups' ethnic homeland. In summary, $\textit{Resources in Ethnic Homeland}_i$ serves as a proxy of γ in the model. The data collected provide variation in the resources that each group controls within its ethnic homeland. Furthermore, exogenous fluctuations in international prices cause the value of resources to change. To capture the fluctuation in the value of resources, I normalized prices of commodities so to have a single price index capturing the effect of the overall market fluctuation at time t $p_t = \sum_k p_{t,k}$, (with $p_{t,k}$ being the price of commodity k in t). Therefore, the interaction term is computed as the sum of interactions: $PriceIndex \times \textit{Resources in Ethnic Homeland} = \sum_k p_k \times Mine_k$. Therefore, I can identify whether some of the conflict events in the country are driven by sudden changes in the value of resources controlled by armed groups as well as by (endogenous) changes to armed groups' defensive capacity as predicted by the findings in Section 2.2.1.

Figure 2.1 displays evidence that the three pure-strategy MPE, discussed in Section 2.2, describe well how the Myanmar's government consolidated its power over the period 1989-2015. The figure plots conflict events between the Myanmar government and three armed groups over time (out of the forty-seven present in the country). The solid green line shows that the Myanmar government, throughout this period, is always fighting against the Karen National Union. On the contrary, the Pa-O National Organization, represented by the yellow dashed line, is never attacked. Lastly, the Myanmar National Democratic Alliance Army is attacked only in recent years when the ceasefire signed in 1989 broke following an offensive from the Myanmar government. All these patterns are consistent with Propositions 2.1 to 2.3.

Before showing evidence from regressions, I discuss anecdotal evidence to explain how the variables of interests capture the decision making process of the Myanmar govern-

Figure 2.1: **Yearly Conflict Events between the Myanmar government and Three Armed Groups**



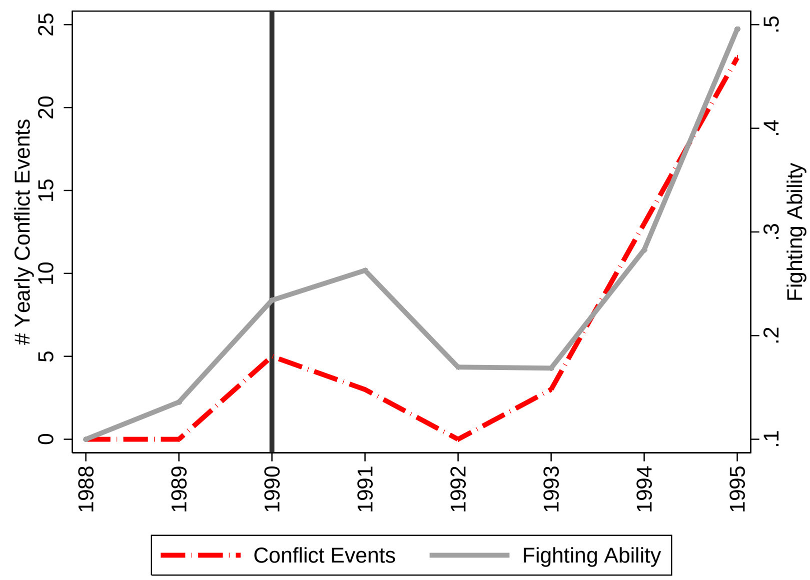
Source: UCDP 3.0 Georeferenced Event Dataset and Myanmar Peace Center Records. The armed groups in the picture are, respectively, the Karen National Union (KNU), Pa-O National Organization (PNO), Myanmar National Democratic Army (MNDAA).

ment.[9] The the *Shan United Army* (henceforth, SUA) was an armed group that agreed to a peace deal with the government throughout the eighties. During this time, the group rose to prominence buying the opium harvest from smaller armed groups and smuggling it to Thailand through its territories controlled along the border. At the beginning of the nineties the group became too influential among other groups and the Myanmar government launched an offensive against it. The dashed red line in Figure 2.2 shows the yearly conflict events between the SUA and the Myanmar government between 1988 and 1995. The solid gray line shows the normalized defensive capacity as predicted from the network of alliances of the SUA. The vertical black line denotes the year in which the ceasefire between the Myanmar government and the SUA ceased. The prominence among the network of armed groups is captured by the SUA's rising fighting capacity at the end

[9]Sources for this anecdote are, respectively, Lintner (1999), Smith (1999) and South (2008).

of the eighties.

Figure 2.2: **Yearly Conflict Events between the Myanmar government and the SUA (1988-1995)**



Source: UCDP 3.0 Georeferenced Event Dataset and Myanmar Peace Center Records. The armed group in the picture is the Shan United Army (SUA).

2.4.2 OLS Results

In what follows, I show preliminary evidence that the patterns of conflict and ceasefire deals between the Myanmar government and the various armed groups follow the comparative statics results discussed above. These results should be taken with a grain of salt: as the Defensive Capacity of each group is derived from the network of alliances and enmities between armed groups, the network structure might respond to fighting activity that occurred in the past. An additional challenge, when testing the model's predictions, is to observe how the distribution of power changes over time between the Myanmar government and the various armed groups. Despite these limitations, the data allows to test 2.5, that is, positive shocks to natural resources make conflict more likely and stronger groups are more likely to experience violent monopolization of power over peaceful one.

$$
\begin{aligned}
y_{i,c,t} = \; & \delta + \beta \text{ Defensive Capacity}_{i,t} \; + \; \boldsymbol{\gamma} \text{ Resources in Ethnic Homeland}_i \; + \\
& + \boldsymbol{\psi} \text{ Price Index}_t \times \text{Resources in Ethnic Homeland}_i \; + \; \theta_t + \boldsymbol{\rho y_{i,c,t-1}} \; + \\
& + \kappa \text{Geog.Controls}_c \; + \; \chi \text{Rain Season Drought}_{c,t} + \text{district}_i \; + \; \eta_{i,c,t} \qquad (2.1)
\end{aligned}
$$

In column (1) of Table 2.2, I estimate equation 2.1 using a linear probability model. The sample is composed of geographic cells of size 0.25×0.25 decimal degrees (roughly 16× 16 miles) in which armed groups are present (i.e. where the Myanmar government does not have the monopoly of violence). The dependent variable is $y_{i,c,t}$ which equals one if cell c, controlled by armed group i during month-year t is attacked by the Myanmar government. The three right hand side variables of interest are: the *Defensive Capacity*$_{i,t}$ of armed group i at time t, the *Resources in Ethnic Homeland*$_i$ and its interaction with the normalized price vector (Price Index$_t$ × Resources in Ethnic Homeland$_i$). According to the model's prediction, the coefficient on the interaction between a price index of international commodities with *Resources in Ethnic Homeland*$_i$ should be positively related to the decision of the Myanmar government to attack the armed groups where resources are located (this follows from Propositions 2.4 and 2.5). Following Proposition 2.5, the Myanmar government should attack more often rebel groups with higher *Defensive Capacity*$_{i,t}$. The baseline specification includes a vector of cell-level geographic controls (labeled *Geog.Controls*$_c$ in equation (2.1) such as roads, average slope within the cell and a dummy if the cell is along the border with one of the neighboring countries. The effect of weather shocks is captured by the inclusion of a dummy called *Rain Season Drought*$_{c,t}$ taking value one if the cell experienced a drought during the last rain season. $\boldsymbol{y_{i,c,t-1}}$ in equation 2.1 denotes six dummies for conflict occurrence within cell c during the last six months (i.e. one dummy for each month). *district*$_i$ is a fixed effect controlling for time invariant district (geographical) characteristics.[10] Coefficients in Table 2.2 (column (1)) should be interpreted as expected percent change in the probability of conflict with respect to a one standard deviation increase in the independent variable. Results in Table 2.2 show that a one standard deviation increase in a group's Defensive Capacity is associated with an expected increase in the probability of conflict with the Myanmar government by 0.139% (over a baseline yearly probability of 1.1%). In column (2) of the same Table, I use monthly data to estimate the same equation with the dependent variable being a dummy that equals one whenever the Myanmar government and armed group i agree on a ceasefire (and zero if the two parties do not conclude a ceasefire or if fighting between them resumes). Results confirm the results of Proposition 2.5, groups with lower Defensive Capacity and with fewer resources in their ethnic homelands are less likely to conclude a ceasefire deal with the Myanmar government. In particular, a one standard deviation decrease of a group's defensive capacity reduces the probability of a ceasefire being signed by 0.05 per cent. A result in column (2) that stands out with respect to column (1), is that, in line with Proposition 2.4, the *level of resources* that a group has in its ethnic homeland (i.e. γ in Section 2.2) the less likely the group is to sign a ceasefire with the government.

[10]Districts are administrative regions within Myanmar states, there are fifty districts in the sample.

Table 2.2: **Correlation between Conflict, Commodities' Shocks and Defensive Capacity**

Estimates from Linear Probability Model

Dependent Variable:	Dummy for Monthly Conflict (1)	Dummy for Monthly Ceasefire (2)
Defensive Capacity	0.139**	-0.056***
	(2.231)	(-3.499)
Price Ind.$\times$ Resources in Ethnic Homeland	0.296***	-0.057***
	(4.649)	(-10.226)
Resources in Ethnic Homeland	0.112	-0.066*
	(1.417)	(-1.873)
# Observations	195,641	195,641
# Clusters	153	153
Adj. R-Sq.	0.163	0.438
Month F.E. $\times$ Year F.E.	Yes	Yes
District F.E.	Yes	Yes

Coefficients from Linear Probability Model show the expected percent change in conflict probability with a one standard deviation change in the indep. variable. The baseline probability of conflict in a year is 1.16%. T-statistic in parentheses from S.E. clustered at the township level (153 clusters). Estimation period: monthly data from Jan 1989 to Dec. 2015. Controls in every regression include Fixed Effects for District, Indicator for below average rainfall during the previous rain season, cell average slope, border dummy. Both specifications includes six dummies for lagged conflict within the cell in the previous months. * p<.1, ** p< .05, *** p< .01

2.5 Conclusion

In this chapter, I show that the Myanmar government's efforts are consistent with the prediction of as model in which absence of commitment creates a trade-off that causes peaceful versus violent consolidation to emerge as equilibria. These findings help to bridge the gap between theoretical models of conflict and empirical evidence Blattman and Miguel (2010). Moreover, results shed light on the particular type of bargaining failures that lead to conflict. In their review, Jackson and Morelli (2011) list commitment problems as one of many possible sources of bargaining failures with asymmetric information, indivisibilities of the spoils of the war and agency problems being the others. In the context of Myanmar, indivisibilities seem to be unlikely to be a major problem as the government and rebel groups often share the resources during peaceful periods. While asymmetric information may have played a role in the onset of the war, my analysis starts forty years after the beginning of the war. All authors documenting the evolution of the war state that ethnic leaders, since the eighties, were aware that they stood no chances to defeat the government through military operations (see Buchanan (2016) Oo and Min (2007), Jolliffe (2015)).

One of the main result of this chapter is to show that peaceful consolidation takes time. Indeed, the inability to commit is such that some groups are unwilling to accept a distribution of power that favors the government in a small time interval. Moreover, because the defensive capacity of a group depends on its alliances and enmities exogenous shocks to the network structure have far reaching consequences on the strategy of the government. The collapse of the CPB as well as of the MTA affected the balance of power so to trigger new ceasefire deals to be signed and old ones to unravel.

Chapter 3

Horizontal vs. Vertical Transmission of Fertility Preferences

3.1 Introduction

Over the last fifteen years, economists have shown growing interest in the effect of culture on outcomes, social norms and traits such as living arrangements, labor force participation, level of trust and fertility decisions just to name a few.[1] However, the mechanism through which culture is transmitted is still a black box, for culture can be very "sticky" or rapidly evolving according to the social norm of interest (see Giavazzi et al. (2014) for a recent discussion). Following the seminal contribution of Bisin and Verdier (2001), papers documenting the persistent effect of culture have generally not been able to distinguish between the transmission channels through which the persistence in social norms occurs. In fact, (Bisin and Verdier, 2001) mention two distinct channels: the vertical one, that occurs from parents to children, and the oblique-horizontal one from peers (henceforth, I will simply refer to the latter channel as the horizontal one). In their model parents exhibit "imperfect empathy": their utility function is affected by children's choice to pick up one of the two social norms in the society.[2] Since parents' utility is increasing in their own social norm, they are willing to incur a cost in order to maximize the probability of children acquiring the parental social norm. Moreover, the socialization effort exerted by the parents decreases the larger its social group as the two channels substitute each other.

Previous empirical work studying the transmission of social norms across second generation immigrants has generally taken different approaches to measure the transmission of social norms among second generation immigrants.[3] The most popular of these is

[1] See Guiso et al. (2011, 2006) for a thorough review on the effect of culture on several outcomes.

[2] In their model (Bisin and Verdier, 2001) assume that a monoparental family has one child which is born without one of the two existing cultural traits $\{a, b\}$. Parent chooses the optimal socialization effort level having perfect information of how many individuals in the population share its social norm.

[3] Henceforth in this paper, second generation immigrants are defined as U.S. born with at least one foreign born parent. First generation immigrants, i.e. those immigrants that were born outside the U.S., are here called foreign-born immigrants.

the epidemiological approach which I adopt in what follows. According to this strategy, the key explanatory variable capturing the persistence of preferences and social norms among immigrants and (or) their children should be measured in the country of origin of the parents that migrated (henceforth *source country* in this article) in order to reflect the prevailing social norm of interest.[4] However, a careful analysis of the previous literature shows that the choice of such variable has generally been limited by data availability. For instance, Alesina and Giuliano (2010), Algan and Cahuc (2010) and Ljunge (2014) use the same World Value Survey's waves to obtain dependent as well as independent variables when using the epidemiological approach. While this strategy generally shows that cultural norms play a role in determining several outcomes, it is problematic as it does not shed light on the transmission channel through which cultural norms persist.

My approach takes one step forward in trying to unravel what is the transmission mechanism that leads to cultural persistence. Focusing on individual fertility decisions of second generation married women living in the U.S. between 1910 and 1970, I perform a "horse race" between the vertical and horizontal transmission channels of preferences in Bisin and Verdier (2001). The former channel is measured using lagged values of marital fertility rates in *source country s* (hereinafter $MFR_{s,t-30}$ where t is the Census year in which a second generation woman is surveyed) as explanatory variable for the number of children a second generations woman had in her life. The reasoning underlying this choice is that, in presence of vertical transmission, I expect the number of children of second generation women to be correlated with the MFR measured in their source countries at the time of migration of their parents. Measuring the horizontal channel, that is the transmission of values from foreign-born peers that migrated from the same source countries to second generation women, is more challenging. In fact, because of the reflection

[4]See Fernández (2011) for a review of the advantages and drawbacks of this method. Other methodologies include the dummy variable approach (see Giuliano (2007) for an example), others have approximated the social norm simply averaging across migrants' population (Borjas (1995, 1992) Card et al. (2000) provide examples of such studies).

problem ((Manski, 1993)) one cannot plug in the $MFR_{s,t}$ computed among peers in the U.S. at the time of the Census. Hence, I use contemporaneous values of Marital Fertility Rates in the source countries (i.e. $MFR_{s,t}$) as a measure of the horizontal transmission of fertility preferences from foreign-born immigrants that migrated from Europe one generation after the parents of the second generation women in the sample. During the time window analyzed (1910-1970 U.S. Censuses) fertility rates underwent sharp changes in the source countries. Hence, the autocorrelation of MFR is low and this enables the inclusion of both $MFR_{s,t}$ and $MFR_{s,t-30}$ in the same model. This strategy is possible as I have a unique source documenting fertility decisions for almost one hundred years (i.e. from 1880 to 1970) in almost thirty European countries before and after the first fertility transition occurred Coale and Watkins (1986).

As I use data from multiple U.S. Censuses, the longitudinal dimension allows me to control for a set of fixed effects that purge results from time-invariant unobservable characteristics. In the most demanding estimation, I include a fixed effect that captures MSA × year specific unobservables thus controlling for geographical and year level effects that might influence fertility decisions. Although I cannot fully test for the extent to which women in the sample are exposed to the influence of peers from the same source countries over their lifetime, I take advantage of the variation stemming from U.S. Metropolitan Statistical Areas (henceforth MSAs) having a greater (or smaller) fraction of newly arrived foreign born migrants relative to the population of second generation peers.[5]

In order to run the horse race, I use a pooled Negative Binomial model. While my results confirm past findings about the effect of cultural norms on family size (Fernández and Fogli (2009, 2006)), I find mixed evidence of both channels of transmission playing a

[5]Results' internal validity is still challenged by the potential presence of time-varying unobservables. Previous studies relying on cross-sectional data such as: Fernández and Fogli (2009, 2006), Alesina and Giuliano (2010), Ljunge (2014) are potentially affected by the presence of both time varying and time invariant unobservables.

role.[6] In line with the theoretical results in Bisin and Verdier (2001), I find that the presence of foreign-born married couples within the same MSA is strongly correlated with the horizontal transmission of fertility norms. Therefore, second generation women living in MSAs that underwent inflows of foreign born immigrants ended up having preferences that were closer to their peers in the source country rather than their parents' ones. Conversely, whenever an MSA did not experience inflow of foreign born peers, the vertical transmission channel dominates over the horizontal one. Since I do not observe where the women in the sample were born and lived before filing the Census, I cannot completely rule out that my results are driven by self-selection of immigrants into areas with a high (or low) density of foreign-born immigrants. If this is the case, my estimates are likely to be an upper bound of the horizontally and vertically transmitted cultural effect.

The rest of the paper is organized as follows: Section 3.2 reviews the literature about cultural transmission of preferences with a special focus on the studies looking at second generation migrants and using the epidemiological approach. Section 3.3 describes Coale and Watkins (1986) data on fertility. Moreover, this section explains how individual data on married couples was chosen for Censuses from 1910 to 1970. Section 3.4 explains the identification strategy adopted together with its advantages and drawbacks with respect to what has been done in the past. Section 3.5 shows the results of the pooled Negative Binomial estimation and suggests a potential channel through which the transmission of preferences observed in the data occurred. Section 3.6 concludes.

[6]The persistent effect of fertility preferences is such that an increase of one child in the *source country* marital fertility rate is associated with an increase by a factor of 1.07 in the number of children a second generation woman had.

3.2 Literature Review

Previous work attempting to single out the role of culture on a set of diverse outcomes has used foreign-born migrants and, more often, their children.[7] Guiso et al. (2004) were among the first to use migrants data to show that, within Italy, variation in the level of social capital had a causal impact on the use of formal credit and checks. However, differences in choices among foreign born migrants might reflect an "endowment effect", that is, they might be partially caused by early life experiences such as growing up in places with different institutional environments. In order to address this criticism, in a series of original articles Fernández and Fogli (2006, 2009) analyzed fertility choices and labor force participation of second generation women in the U.S. Indeed, differently from their parents, migrants' children who were born and raised within the identical institutional environment of a single country, represent the ideal individuals on which is possible to test the persistence of preferences inherited from their parents. In a series of articles, the authors showed that fertility and labor force participation (henceforth abbreviated with LFP) measured in the 50's in the *source country* explains the variation in preferences for the number of children as well as for LFP's decision of second generation's migrants women.[8] This attempt to single out "cultural" from "environmental" beliefs using a variable measured in the country of origin of the parents is called epidemiological approach and has now been adopted widely in economics.[9] At the same time of Fernández and Fogli (2006, 2009) other articles showed that the heterogeneity in outcomes and choices of second generation's migrants within the U.S. is accounted for by the variation at the parents' country of origin level. Namely, Giuliano (2007) for instance, shows that impor-

[7] Guiso et al. (2006) define culture as *the set of customary beliefs and values that ethnic, religious, and social groups; transmit fairly unchanged from generation to generation* , for a thorough discussion see Guiso et al. (2011).

[8] The authors use information on the country of origin of the father to define the *source country* of second generation women observed in the 1970 U.S. Census and in multiple GSS waves.

[9] See Fernández (2011) for an introduction to the epidemiological approach.

tant decisions such as living arrangements of second generation's migrants in 1970's and 2000's are highly correlated with the ones in place in the country of origin of the parents. Similarly, Alesina and Giuliano (2010) use the beliefs about the family from the World Value Survey as a proxy for second generation's "cultural baggage" inherited from their parents. The authors demonstrate that culture has high explanatory power with respect to women's as well as youth's LFP measured from the CPS data and the American Time Use Survey. Furthermore, the authors also find that the "cultural baggage" variable affects a wide array of choices such as: family size, home production, living arrangements and geographic mobility of second generation migrants.

Since the sample of analysis consists of a cross-section of individuals, these articles also face some limitations due to the absence of the longitudinal dimension. For instance, it is impossible to control for place-of-origin unobservable characteristics that might be driving the results through a spurious correlation. Algan and Cahuc (2010) were able to control for *source country* unobservables by looking at different cohorts of immigrants' descendants over time. In order to study the effect of trust on GDP per-capita growth in a set of countries, the authors estimate values of trust for the beginning of the twentieth century (1910) by looking at GSS answers of second, third and fourth generation U.S. citizens whose parents moved to the U.S. around 1910. Provided that the transmission of trust is vertical (i.e. from parents to child) and that immigrants' descendants are not influenced by shocks occurring in the *source country* after their ancestors left, the trust level should differ over consecutive cohorts of immigrants. The main problem of the paper lies in the fact that the transmission of trust across generations need not be vertical. Different sources of transmission can occur through the interaction with newly arrived immigrants from the same *source country* of their ancestors. Alternatively, higher generations could be assimilating and simply reflect the trust level of the country in which they are living.

As a matter of fact, Bisin and Verdier (2001) show that there are multiple channels through which heterogeneous preferences can persist over time. In their model, the authors hypothesize the existence of two channels of transmission: vertical (i.e. through the parents) and horizontal-oblique (i.e. through peers, teachers etc.) and show that both substitutability and complementarity among the two channels can sustain stationary states in which heterogeneous traits persist in the population. In light of this theoretical result, one cannot be sure that a second or higher generation immigrant will acquire his social trait *exclusively* from his family. In fact, if consecutive generations from the same *source country* have different social traits, socialization among them will increase the probability of acquiring a trait that differs from the one of their parents.

Mostly because of data shortage, studies documenting the persistent effect of cultural norms on preferences and choices could not check for the presence of these two channels. Fernández and Fogli (2009, 2006) for instance, use 1950 female LFP and fertility from a set of *source countries* as epidemiological variables explaining the variation in economic outcomes between women aged thirty to forty years old in 1970. Therefore, 1950 is not an ideal choice as their parents were certainly born at the beginning of the century when values for women LFP and fertility were certainly different and, because of the fertility transition, not highly correlated with the values observed in 1950. Hence, from their studies, it is not clear which transmission channel among the vertical and the horizontal one is driving the correlation. By the same token, many articles applying the epidemiological approach suffer from this problem: Alesina and Giuliano (2010) for instance, employ the independent variables as well as the key right hand side one from surveys conducted roughly at the same time. Among the recent literature, Ljunge (2014) studies the inter-generational transmission of trust among the children of immigrants in several European countries. Unfortunately, the author measures trust in the source countries, i.e. the epidemiological variable, through waves of the World Value Survey that are collected at the same time of the ones measuring trust among second generation, i.e. the dependent variable. In the same way, Algan and Cahuc (2010) use trust measured in the parents' source countries as independent variable to estimate the inter-generational transmission of this value among second and higher generation of migrant in the U.S. However, both the left and right hand side variables are again measured at the same time using World Value Survey waves. Finally, Giavazzi et al. (2014) analyze the convergence of a set of values among immigrants up to the fourth generation within the U.S. and finds substantial heterogeneity in this process. Namely, the authors show that persistence is specific to some topics such as religious ones as well as linked to descendants whose ancestors came from specific countries.

3.3 Data Description

3.3.1 Fertility Data for European Countries 1880-1970

I use data on marital fertility from the following source: *The decline of fertility in Europe: the revised proceedings of a conference on the Princeton European Fertility Project* (Coale and Watkins, 1986), which to date represents the most complete source of information on European fertility during the nineteenth and early twentieth centuries. The main goal of this study was to date the onset of the fertility transition in every European region. Specifically, for every country s and different years t, this source includes the Marital Fertility Rate. Coale and Watkins (1986) also reports another variable: I^g_{st} which is a ratio of the number of births occurred to married women divided by a hypothetical fertility plateau that would be reached if all women in the population were to adopt the Hutterites' fertility schedule.[10] Throughout the rest of the paper I use MFR_{st} as right hand side variable,

[10] The Hutterites are an Anabaptist sect that migrated from Europe to the north central regions of the U.S. as well as south central Canada in order to avoid religious persecution. Since any sort of contraception or abortion is strictly forbidden within this sect, their Fertility rate is taken as an upper bound by Coale and Watkins (1986). Additional details on how the variables are constructed are included in the Section B.1 of the Appendix.

I also replicate my analysis using I^g_{st} in the Appendix's Section B.3. Data frequency differs by country, France, for instance, has data from 1831 until 1961. Other countries like Romania and Bulgaria have only three data points starting from 1900 and ending in 1956. In general, most of the countries in the sample have at least four different observations divided by a 30 years lag between each other starting from 1880 until 1970.[11]

I use these data exclusively to have a measure of the MFR for almost thirty countries in a time window of almost one hundred years. Since the first fertility transition occurred in Europe mostly during the second half of the nineteenth and the first half of the twentieth centuries this implies that, as shown in Table 3.1, the autocorrelation of MFR_{st} (as well as I^g_{st}) is relatively low when these variable are opportunely spaced using lag of 30 years.[12]

Figure 3.1 shows the variation in the MFR data for four countries for which the frequency is particularly high. As it is evident, fertility rates are sticky when observed over short (ten years') intervals, however, once they are opportunely spaced over thirty years intervals, the figure shows more longitudinal variation.

Table 3.1: **Autocorrelation of the two variables with a 30 years lag**

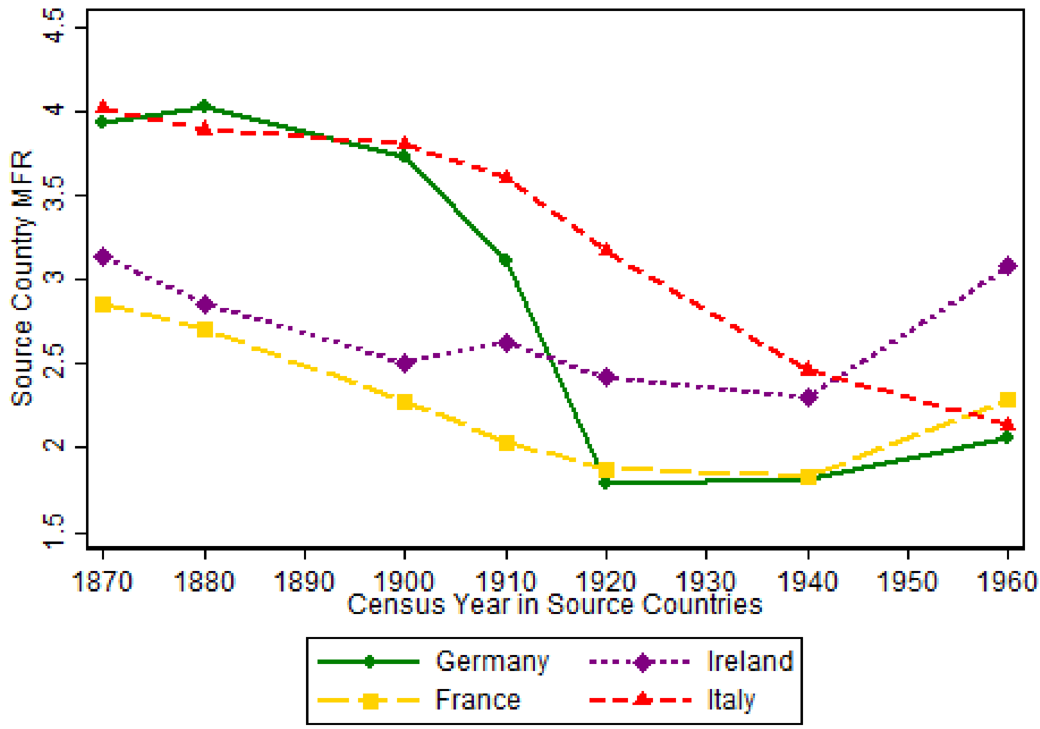
	MFR_{st}	I^g_{st}
MFR_{st-30}	0.5536	
I^g_{st-30}		0.7436

An obvious limitation of using data aggregated at the national level is losing the within country heterogeneity dimension. As suggested by Spitzer and Zimran (2013), one should be careful in using national averages when making inference on a heterogeneous population. Indeed, Coale and Watkins (1986) collected data at a finer level than

[11] Table B.2 in Appendix B.1 shows data availability for the countries in this study.

[12] The choice of 30 years can also be interpreted as a "generational" lag.

Figure 3.1: **Marital Fertility Rates over time for four countries**



Source: author's calculation using data from Coale and Watkins (1986).

the national one (a pattern visible in Figure B.1 in the Appendix). In general, in my study, I am unable to take advantage of the within country variation displayed in this source. However, the within country dimension allows me to have fertility data for regions that later became countries such as the Baltic states, Czechoslovakia and Yugoslavia. A within country analysis would require building a matching algorithm that infers the region of origin of the parents based on their last names, a fact that is clearly impossible for women since their last name changes after marriage. Table B.1 in the Appendix Section B.1.1 replicates one of the main regressions of (Fernández and Fogli, 2009) using (Coale and Watkins, 1986) data showing that results are comparable to the ones she obtained using her dataset.

3.3.2 Data on Fertility in the U.S. 1910-1970

I use individual information on married women born in the U.S. with at least one foreign born parent from the following Censuses: 1910, 1940, 1950 and 1970.[13] I restrict my sample to married women between 20 and 50 years of age as Coale and Watkins (1986) computed their variables using the same age group.[14] The choice of the Censuses is led by the presence of the following variables that are important for the empirical analysis: number of children that a woman had at the time she was filing the Census, within-state geographical identifier, place of birth of the parents and husband's presence within the household. As I am studying the fertility choices of women in different age groups, I cannot use the 1920 as well as the 1930 Censuses as they only ask the number of children living within the household at the time the Census was filed.[15] I could not use the 1960 Census as it lacks detailed geographical identifiers. Similarly, it is not possible to use later Censuses (i.e. 1980 onward) as they lack data on parents' country of birth, while the CPS fertility supplement has this data, the sample size of each wave is dramatically reduced to four thousand individuals.

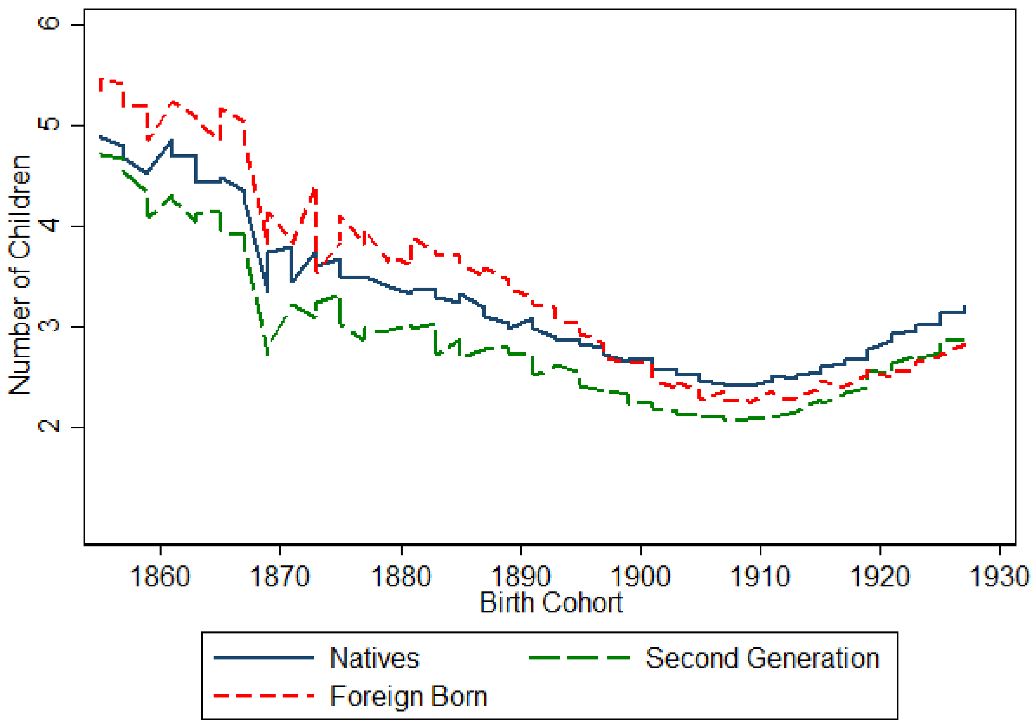
In Figure 3.2 I plot the completed fertility for women in different birth cohorts disaggregated by nativity status. Overall, this figure shows that the data on the number of children that second generation women had display a common trend with respect to natives and foreign born immigrants. However, plotting the completed marital fertility rates by *source country*, as it is done in Figure 3.3, shows that there are persistent differences over time within second generation immigrants. A detail to bear in mind, when

[13]For every year I downloaded the 1% sample from IPUMS, for 1970 the sample I used the 1 % Metro fm2 one.

[14]I understand that the age distribution of the European countries during the years for which the variables were constructed affects their values and might well differ from the age distribution of second generation women in the U.S. observed in the Censuses.

[15]This would imply that for the women in the age group 40-50 years old I would systematically underestimate the number of children they had as some of them might have already moved out of the household.

Figure 3.2: **Number of Children for Different Birth Cohorts: Natives and Immigrants**



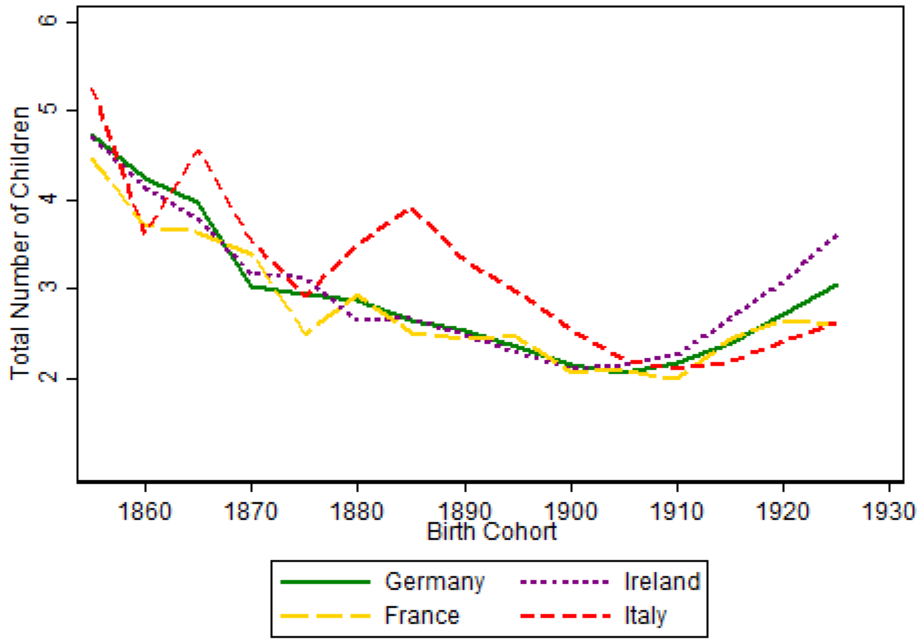
Source: author's calculations selecting women older than 49 in the 1900, 1910, 1940, 1950 and 1970 Censuses.

looking at Figures 3.2 and 3.3 is that these data are taken from consecutive cohorts of second generation women whose parents' social and economic background might differ. As the composition of immigrants changed over time, the sample reflects the variation in migrants' source countries over time.

Every column of Table 3.2 shows, in percentage terms, the sample composition by source country in each Census included in the study. That is the sample of second generation women in 1910 is mainly composed by Germans, Irish and English.[16] This is because the early comers in the U.S. were mainly from these three countries while at the beginning of the twentieth century immigrants came disproportionately from Eastern

[16]In Table 3.2 I select second generation women as having at least one parent foreign born and when both parents are foreign born and come from two different countries I assign the woman to belong to the mother's source country see Table B.3 in the AppendixB.2 to have a full list of women whose parents were foreign born.

Figure 3.3: **Number of Children for Second Generation Women from Different Source Countries**



Source: author's calculations selecting women older than 49 in the 1900, 1910, 1940, 1950 and 1970 Censuses.

and Southern Europe.[17] This pattern can be seen in the following Censuses where the fraction of women whose parents came from countries like Poland, Italy and Russia increases. As the U.S. Census never asked question on religiosity, I am certainly missing this important dimension of heterogeneity by only looking at country of origin of the parents. As a matter of fact, Irish fertility differed according to the religious faith (a fact that is somewhat visible from Figure B.1 where the regions nowadays part of Northern Ireland have lower values of I_g in 1900). In order to remove the descendants of Jewish immigrants from the sample I follow Angrist (2002) and look at Census question on the mother tongue (as well as mother tongue of the parents for those in 1910 Census) so that I can remove all native Yiddish and Hebrew speakers.

[17] For more details on the Age of Mass Migration and immigrants composition over time see Hatton and Williamson (1998).

Table 3.2: **Sample composition by year: selected countries in % of the total sample**

Countries	**Census year**				
	1910	1940	1950	1970	Total
Scandinavian Countries	6.5	11.7	10.1	7.3	8.6
England	11.8	7.7	5.7	5.3	7.6
Scotland	3.1	2.2	1.9	2.5	2.5
Ireland	22.6	9.2	6.9	5.7	11.3
Italy	0.9	10.1	17.3	23.7	13.6
Austria	2.0	3.7	5.6	4.5	3.9
Czechoslovakia	0.1	2.8	3.1	3.7	2.4
Germany	45.3	24.6	13.8	8.3	22.5
Poland	0.2	8.6	12.4	12.3	8.4
Baltic States	0.0	1.2	1.8	1.8	1.2
Russia	1.0	8.0	10.9	10.6	7.6
# of Second Gen. Women	22,761	13,102	18,713	24,514	79,090

Source: 1910, 1940, 1950 and 1970 1% US Census

3.4 Empirical Strategy

3.4.1 Identification and Challenges to Internal Validity

In this paper I apply the epidemiological approach to study the persistence of cultural heritage on fertility choices of second generation migrant women during the period 1910-1970. As discussed in Section 3.2, this identification strategy uses a variable measured in the source country to capture the effect of the "cultural heritage" on a certain outcome. This approach relies on the assumption that there is no omitted variable systematically correlated across different countries, if this is the case, then the epidemiological approach fails as the key right hand side variable might be capturing a spurious correlation driven by the omitted variable.[18]

The main difference between my reduced form identification strategy and previous articles using a similar approach is that I take advantage of the longitudinal dimension of

[18]See Fernández (2011) for additional details on the caveats of using the epidemiological approach to identify the transmission of preferences.

the dataset in order to purge estimates from time-invariant unobservables. The variation in fertility rates over time is a product of the long time frame considered as well as of the differential timing in which the first fertility transition occurred among European countries. Moreover, I argue that this feature allows me to shed light on the mechanism underlying the preference transmission.

Throughout the paper, the dependent variable is the number of children ever born observed at the individual (i.e. married woman) level. As shown in Table 3.2 the sample is composed of more than seventy nine thousand observations. However, the empirical estimation relies on the variation observed at the country-year level. Since the outcome of interest is a discrete nonnegative integer, I estimate a count data model as it is more interesting to understand the effect of the epidemiological variables on having one, two or more children rather than being able to tell what is the effect of the conditional mean. In order to address overdispersion of the dependent variable I run a pooled negative binomial model.[19] I list the regressors of matrix $\boldsymbol{Z}$ in equation (NB2) in more detail in equation (1) and discuss them below.

$$\boldsymbol{Z}'\delta + \epsilon_i = \alpha_s + \boldsymbol{\gamma}_1^{'}\boldsymbol{X}_{it} + \beta_1\left(MFR_{st}\right) + \beta_2\left(MFR_{s(t-30)}\right) + \tau_t + r_m + \epsilon_{ismt} \tag{1}$$

In order to test the cultural transmission of preferences I run a "horse race" between contemporaneous MFR (i.e. MFR_{st} in equation (1)) and lagged MFR (that is $MFR_{s(t-30)}$

[19]Equation (NB2) shows the general expression of the Negative Binomial model:

$$\begin{aligned} f\left(y_i|\boldsymbol{Z}_i u_i\right) &= \frac{e^{-(\boldsymbol{Z}_i u_i)}(\boldsymbol{Z}_i u_i)^{y_i}}{y_i!} \\ \boldsymbol{Z}'\delta + \epsilon_i &= \ln\lambda_i + \ln u_i \\ \mathbb{E}\left(y_i|\boldsymbol{Z}_i, \epsilon_i\right) &= \exp\left(\boldsymbol{Z}_i'\delta + u_i\right) \end{aligned} \tag{NB2}$$

The Negative Binomial estimation requires assuming that the individual heterogeneity term $\exp^{\epsilon_i} = u_i$ is distributed as a Gamma (with parameters $\alpha = \theta \;\; \beta = \theta$) so that the conditional mean of y_i given $\boldsymbol{Z}_i$ equals to λ_i. See Cameron and Trivedi (2013) for a discussion on the Negative Binomial model. For robustness, in Section B.3 of the Appendix I present results when a pooled OLS is used.

in the same equation) measured in the parent's *source country*. The subscript t labels the year in which the MFR has been measured in the *source country*. That is, in order to explain fertility choices of women in the sample, I include two observations of the MFR measured with a lag of thirty years. For example, a second generation woman of French ancestry observed in the 1910 Census will have a value of $MFR_{s(t-30)} = 2.70$ (i.e. the recorded MFR for France in 1880 retrieved from (Coale and Watkins, 1986)), this variable is included to capture the vertical transmission of preferences. The rationale for doing so is the following: if transmission of fertility preferences occurs from parents to daughters, then the MFR in 1880 is the closest measure of the fertility norm of the parents. Besides, the same woman is assigned a $MFR_{st} = 2.03$, which is the MFR for France in 1910 and measures the horizontal transmission of preferences that the woman experiences from her interaction with French born immigrants. The choice of the thirty years lag reflects the change of fertility norms across two generations, this can also be seen from Figure 3.1 where I plotted the change of MFR for France and other three countries over time. Note that, while most papers reviewed in Section 3.2 provided a great contribution in showing the presence of cultural transmission among second generation immigrants, they are unable to distinguish among the two channels as the right and left hand side variables are generally measured during the same time window in Alesina and Giuliano (2010), Fernández and Fogli (2006, 2009), Ljunge (2014). Therefore, authors of these papers mostly emphasize the role of parents in the inter-generational transmission while this article attempts to distinguish between the two. The variation in fertility at the source country level is crucial as the relatively low autocorrelation of MFR allows me to use, for each woman in the sample, two distinct observations of it as proxies for distinct channels of fertility preferences' transmission. In particular, measuring the horizontal channel vis-à-vis the convergence of fertility norms towards the natives' ones is complex as an alternative approach that would use the observed MFR among foreign born immigrants and natives currently living in the U.S. would suffer from the reflection problem ((Manski, 1993)). In the next paragraphs I discuss the explanatory variables used in the estimation as well as how the time dimension allows me to control for the fertility rates at the MSA-year level.

The dependent variable y_{ismt} is the number of children ever born to woman i whose parents came from country s, living in MSA m and surveyed in Census t. $\boldsymbol{X}_{it}$ is a set of individual characteristics correlated with fertility measured in Census t. Namely, these variables are: age, a set of dummies for husband's age and a dummy for farm status.[20] The choice of using women from consecutive Censuses suffers from the drawback that some questions changed over time. In fact, the 1910 Census did not ask for the years of completed education of respondents, therefore, I cannot control for this important determinant of fertility. The concern here is that the cultural effect might be upward biased as it is capturing the outcome caused by parents' underinvestment in education rather than fertility preferences *per-se*. Past studies analyzing the intergenerational transmission of fertility have taken different stances on whether including LFP and education status. On the one hand, Fernández and Fogli (2009) control for as many variables as possible thus including LFP status and educational attainment to avoid the upward bias discussed above. On the other hand, (Blau et al., 2013) omit women's education level and LFP status when analyzing preferences' transmission arguing that fertility preference might be the cause leading to the choice of not investing in education (or entering the labor market). The authors argue that if this is the case, their inclusion among the controls biases downward the estimate of the cultural transmission coefficient. I choose to estimate the model above with and without LFP status, since results are generally identical, I only report models in which LFP status is included. In order to have a proxy for family's income, I create a dummy for high earnings occupation based on the occupation score assigned to

[20] I generate husband dummies in 10 years interval, from 25 to 34, then 35 to 44 and so on.

the husband in the household. I compute the sex ratio at the MSA level following Angrist (2002)'s aggregation procedure among *source countries* as well as generating the sex ratio for each individual *source country*.[21]

The advantages of the time dimension in the fertility data are manifold as I can control for time-invariant unobservables both at the geographical and country of origin level. In fact, α_s in equation (1) is a *source country* fixed effect, i.e. it equals one for all second generations women whose parents came from country s. In order to control for Census specific FE I add τ_t in my specification.[22] As the period studied is one of sharp changes in women LFP within the U.S., I include a FE for each MSA labeled with r_m in equation (1) to control for different labor market opportunities at the MSA level.[23]

I also run a more demanding specification where I augment equation (1) interacting the MSA FE r_m with the Census Year FE τ_t, in doing so, I control for unobservables characteristics that change over time at the geographical level. There are, in fact, several factors affecting fertility whose impact might be changing over time such as: infant mortality, female labor market opportunities in the different MSAs.[24] Note that, adding the interaction term $(r_m \times \tau_t)$ is equivalent to add the MFR measured at the MSA-year level, that is, a regressor that absorbs the fertility within the MSAs in different Census years. Namely, the inclusion of this interaction term guarantees that the coefficient estimated on MFR_{st} does not capture the transmission of fertility preferences from natives to second generation women. Instead, the estimated coefficient on MFR_{st} measures exclusively

[21] Whenever a woman lived outside an MSA I computed this value in the smallest identifiable geographical area, that are respectively: counties for 1910 Census, state economic areas (SEA) for 1940 and 1950 Censuses and County Groups (CNTYGP97) for 1970, see IPUMS website for additional details on these variables.

[22] Note that, since my sample does not have as many observations for the 1940 and 1950 Censuses as for the 1910 and 1970 ones, I treat them as a unique Census when adding τ_t. Results with the Census Year FE treating 1940 and 1950 Censuses separately are available upon request and do not change much with respect to those shown in the following Sections.

[23] Fogli and Veldkamp (2011) document the transition of female LFP participation in the U.S.

[24] That is, female labor market opportunities (or child mortality) in Chicago in 1910 are not the same as the ones in Chicago in 1970.

the horizontal transmission of preferences from *source country* peers. Lastly, unobserved human capital transmission from parents as well as variation in women's education level represent a major threat to internal validity as I cannot control for them in the specification above. Since I only have education data from 1940 onward, I replicate the most important estimations excluding the 1910 Census, reassuringly results are unchanged when education dummies are added to the set of covariates in equation (1).

In Section 3.5.1 I first run the horse race to assess what is the prevailing channel of transmission of fertility preferences among second generation women. Following a short discussion of results, I try to explain what is the underlying mechanism and provide evidence about it in Section 3.5.3.

3.5 Results

3.5.1 The Horse Race Contest

In order to show how results and coefficients change when only one of the two MFR is added, I initially run equation (NB2) including only one of the two epidemiological variables among the right hand side ones. Therefore, the first two columns of every table that follows report results when only the peers' fertility (i.e. MFR_{st}) is included among the regressors. In particular, the first column of every table reports the specification without interacting Census year FEs with MSA ones while in column 2 I interact the two FEs with each other.[25] By the same token, the ensuing two columns report results of the two specifications having only lagged fertility ($MFR_{s(t-30)}$) as epidemiological variable. In order to be consistent, columns (3) and (4) have, respectively, the same set of FEs as columns (1) and (2). Finally, the last two columns, i.e. (5) and (6) of each table, display results of the horse race estimation. Standard errors are clustered at the parents' *source*

[25]The bottom of each table has a list of which FE are included in the regression.

country level and reported in parentheses.[26]

[26] Note that significance tests on the Incidence Rate Ratios are run against the null hypothesis that if the regressor has no effect on the number of children ever born then $\exp^{\hat{\beta}} = 1$.

Table 3.3: **Horse Race between Current and Lagged Fertility Norms**

	Dependent Variable Children Ever Born					
	Current Fertility		Lagged Fertility		Horse Race	
	(1)	(2)	(3)	(4)	(5)	(6)
MFR_{st}	1.078***	1.086***			1.060*	1.068**
	(0.027)	(0.027)			(0.032)	(0.029)
MFR_{st-30}			1.069***	1.073**	1.051	1.052*
			(0.027)	(0.030)	(0.032)	(0.031)
Labor force status	0.775***	0.773***	0.775***	0.773***	0.775***	0.773***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
# Countries	27	27	27	27	27	27
# Observations	79090	79090	79090	79090	79090	79090
Log. Pseudolik.	-1.46e+05	-1.45e+05	-1.46e+05	-1.45e+05	-1.46e+05	-1.45e+05
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Year FE	Yes	No	Yes	No	Yes	No
MSA FE	Yes	No	Yes	No	Yes	No
MSA*Year FE	No	Yes	No	Yes	No	Yes

The coefficients shown are marginal effects estimated from a Negative Binomial model, controls include woman's age, age squared, ten years dummies for husband's age group, sex ratio among migrants from the same source country within the MSA in which they live at the time of the Census. The sample is made of second generation married women from the 1910, 1940, 1950 and 1970 U.S. Census. * p<.1, ** p<.05, *** p<.01 S.E. in parentheses clustered at the *source country* of the parents level.

The Negative Binomial coefficients reported in Table 3.3 are Incidence Rate Ratios, i.e. "exponentiated" coefficients ($\exp^{\hat{\beta}}$) that can be given a multiplicative interpretation. The Incidence Rate Ratios of the first four columns show that a one child increase in the *source country's MFR* is associated with an expected increase of the number of children ever born by a factor of 8% (7% for lagged values MFR_{st-30}). When the two variables are horse raced, the lagged measure MFR_{st-30} is marginally significant at the 10% level while the coefficient (and its incidence rate ratio) of the contemporaneous MFR_{st} remains significant and its size decreases only marginally. Overall, Table 3.3 shows that both proxies for MFR explain fertility choices of second generation women. The obvious question stemming from this result is whether the two variables are simply noisy proxy of each other or if the two measures of MFR actually estimate the two distinct channels of preference transmission in (Bisin and Verdier, 2001). Indeed, a Wald test for the equality of the coefficients cannot be rejected in Columns (5) and (6). However, in section 3.5.3 I show that the two variables are capturing different channels of preferences' transmission. In the next section I also address the possibility that results above are driven by measurement error in $MFR_{s,t-30}$.

In Section B.3 of the Appendix I include several robustness checks. The most important of these, addresses the concern that results in Table 3.6 are driven by unobserved human capital among women in the sample. Dropping the 1910 sample, I generate education dummies and replicate 3.6 in order to check if results are unchanged.[27] Results are shown in Table B.4 (Section B.3 of the Appendix) and display that Incidence Rate Ratios on lagged and contemporaneous fertility are greater in magnitude than the ones in Table 3.6. Therefore, not including human capital among regressors causes a downward bias in the estimated coefficients. Besides, I show that results are qualitatively identical if, instead of using a negative binomial model, I run a pooled OLS keeping the right hand

[27]The dummies flag the following education achievement: High School degree, college attendance in the past, college degree or more.

side variables unchanged with respect to the ones in equation (1).

3.5.2 Measurement Error in the Lagged Fertility Rates

A possible criticism to the results of the previous section is that measurement error in the lagged fertility rates (i.e. in $MFR_{s,t-30}$) is causing the variable to be marginally significant as some of its explanatory variable is captured by $MFR_{s,t}$. In order to address this concern, I use an alternative source of historical fertility to implement a control function and instrumental variable approach ((Wooldridge, 1997)).

Table 3.4: 2SLS and Control Function Estimates

	Dependent Variable Children Ever Born							
	OLS	**OLS**	**2SLS**	**2SLS**	**Neg. Bin.**	**Neg. Bin.**	**Poisson**	**Poisson**
MFR_{st}	0.216**	0.220***	0.210**	0.215***	1.096***	1.105***	1.098***	1.105***
	(0.091)	(0.072)	(0.088)	(0.069)	(0.035)	(0.029)	(0.034)	(0.028)
MFR_{st-30}	0.123**	0.128**	0.142***	0.144***	1.036*	1.038*	1.043**	1.044**
	(0.055)	(0.050)	(0.049)	(0.049)	(0.021)	(0.020)	(0.021)	(0.020)
Residuals							0.946	0.951
							(0.075)	(0.073)
# Countries	24	24	24	24	24	24	24	24
# Observations	71317	71317	71317	71317	71317	71317	71317	71317
Adj. R-Sq.	0.169	0.172	0.169	0.172				
Log. Pseudolik.					-1.35e+05	-1.35e+05	-1.33e+05	-1.33e+05
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Year FE	Yes	×	Yes	×	Yes	×	Yes	×
MSA FE	Yes	No	Yes	No	Yes	No	Yes	No
MSA*Census Year FE	No	Yes	No	Yes	No	Yes	No	Yes

The first two columns report estimated coefficient from OLS regression so that they can be compared with the 2SLS of columns (3) and (4). Coefficients shown in columns (5) to (8) are incidence rate ratios estimated using a a Negative Binomial model (5-6) and a Poisson regression (7-8), controls include woman's age, age squared, ten years dummies for husband's age group, sex ratio among migrants from the same source country within the MSA in which they live at the time of the Census. The sample is made of second generation married women from the 1910, 1940, 1950 and 1970 U.S. Census. The row labeled "Residuals" reports the coefficient on predicted residuals obtained from the first stage estimation using $GFR_{s,t-30}$ as an instrument for $MFR_{s,t-30}$. * p<.1, ** p<.05, *** p<.01 S.E. in parentheses clustered at the *source country* of the parents level.

The International Historical Statistics is a compendium of international socio-economic data from 1750 to 2010 (Mitchell, 2003). Among its data these volumes report data on Crude Birth Rates and population breakdown by age and gender for several countries in the world over time. In particular, twenty four out of the twenty seven countries for which (Coale and Watkins, 1986) report data are included in this dataset. Therefore, I compute the Generalized Fertility Rate, hereinafter *GFR*, for every country-year available. The *GFR* is the number of total live births for a thousand women in reproductive age (20-49). This source has both advantages and disadvantages. Among its advantages there is the feature that these data have been published continuously since 1970 and thus purged from possible mistakes in the (Coale and Watkins, 1986) data. As a matter of fact, the authors of (Mitchell, 2003) explicitly exclude some country-years available in the data from the Princeton Population project as they deem them unreliable.[28] The disadvantage of this source is that it does not report Marital Fertility Rates, therefore, is not directly comparable with the data used so far.

I assume a linear relationship between *GFR* and *MFR* so that the former can be used as an instrument for $MFR_{s,t-30}$ and implement a two stage least square estimation in order to show that both the estimated coefficients measuring current and past fertility rates are indeed significant and attenuation bias and autocorrelation are not driving $MFR_{s,t}$ to be significant and its lagged counterpart to be insignificant. Under the assumptions of linear measurement error if the instrument $GFR_{s,t-30}$ is uncorrelated with the error term in (1) the 2SLS estimates will identify the true coefficient. Results are in Table 3.4, the first two columns show the OLS coefficients with the sample reduced to reflect data availability in the instrument' source. These can be compared to the 2SLS results in columns (3) and (4). As usual the 2SLS coefficient is slightly larger than the OLS one but the significance is not affected when instrumenting for $MFR_{s,t-30}$.

[28]This implies that I lose around ten percent of the sample when using the data.

In section 3.5.1 as well as in the remainder of the paper, I use a Negative Binomial model to estimate the transmission channel. Therefore, I provide evidence that results are unchanged when using the Generalized Fertility Rate as an instrument for $MFR_{s,t-30}$. As above I assume a linear relationship $MFR_{s,t-30} = GFR_{s,t-30} * \xi + v_{s,t-30}$ and that $GFR_{s,t-30}$ is uncorrelated with the error term in (1) and $v_{s,t-30}$. I therefore implement a control function approach ((Wooldridge, 1997), (Wooldridge, 2002)) estimating the reduced form first stage relationship between the two variables adding all the controls in (1) and inserting the predicted residuals among the right hand side variables of a Poisson regression that has the same explanatory variables used for the horse race of Table 3.3. The last two columns of Table 3.4 report IRR of a Poisson regression and can be compared to the Negative Binomial coefficient of columns (5) and (6) where I replicate the horse race of the previous table with the reduced sample for which the instrument is available.[29]

3.5.3 Mechanism Underlying the Horse Race Result

The vertical transmission of preferences alone is unable to explain the result in Table 3.3. Indeed, while the significance of $MFR_{s(t-30)}$ is consistent with this channel, this mechanism does not explain the finding on MFR_{st}. As previously found in (Fernández and Fogli, 2009), the role of second generation peers might be important in amplifying the transmission effect of preferences in multiple ways. For instance, the role of social reward or punishments associated with different behavior might vary with the fraction of individuals of the same ancestry living in a woman's neighborhood or city. However, I argue that second generation cohorts alone are unlikely to know what are the prevailing contemporaneous fertility norms in their *source countries*. Because of the particular time

[29] In order to estimate a Negative Binomial regression, I would need to assume that $y_i|v_{s,t-30}$, $MFR_{s,t-30}$ and $GFR_{s,t-30}$ has a Negative Binomial distribution with exponential mean, the Poisson regression does not requires this assumption. Results are unchanged with a Negative Binomial estimation or a GMM approach (results available on request).

frame studied, fertility norms in the *source countries* changed considerably, so that, second generation women (as well as their husbands) cannot "learn" from their parents what the contemporaneous fertility norms are in their *source countries*. In order to substantiate this claim, I construct a variable, called $AncestryRatio$, that is the ratio of second generation immigrants over the total population at the MSA level.[30] Table 3.5 displays that once this variable is interacted with MFR_{st} (or $MFR_{s(t-30)}$), it is not significant in explaining fertility choices of the women in the sample. Moreover, comparing the coefficients of the epidemiological variables in Tables 3.5 and 3.3, it is straightforward to notice that results are not sensitive to the inclusion of these variables.

Since the variation in the presence of second generation immigrants across the U.S. does not explain the transmission effect arising from the data, the natural question to ask is how second generation women in the U.S. are exposed to contemporaneous fertility preferences from their source countries. In order to understand if the channels of transmission causing the two coefficients to be significant are actually distinct from each other, I investigate the role of foreign born immigrants as "catalysts" of the fertility norm measured with MFR_{st}. In other words, I analyze the role of social learning between foreign born immigrants and second generation women in the transmission of fertility preferences. Indeed, differently from second generation immigrants, foreign born ones are directly exposed to the most recent fertility norm of their country as they were born and partially raised abroad. Table 3.6 provides evidence of this as it displays results after estimating the Negative Binomial model of equation (1) on a sample of foreign-born married women. In this case, the horse race has a clear winner as lagged values of MFR are never significant. This result shows that fertility preferences of foreign born immigrants in the U.S. reflect the ones of their overseas peers. Since the data used is based on

[30] Whenever a woman in the sample was not living in a MSA, I computed this figure for the smallest geographical area which were, respectively, counties (in 1910 Census), state economic areas (in 1940 and 1950 Censuses) and county groups (in 1970 Census)

country-year averages, one might be concerned that migrants' self selection might cause the fertility data to be not representative of their realized fertility preferences. Therefore, the result in Table 3.6 bolsters the validity of the data used as it shows that foreign-born immigrants effectively carried a fertility norm similar to their overseas peers.

The role of social learning and behavioral change is not new in the analysis of fertility preferences. In a recent paper, (Spolaore and Wacziarg, 2014) argue that the fertility decline, occurred during the first demographic transition in Europe, was the result of the diffusion of new social norms and behavioral changes from the innovator (i.e. France) to the countries nearby and, gradually, to the rest of Europe. Given the time frame considered, alternative channels of transmission such as television, newspapers and the radio are unlikely to play a decisive role in shaping fertility preferences.[31,32] Moreover, Bisin and Verdier (2001) model provides the theoretical foundation of the proposed channel: the authors show that, parents' socialization effort (i.e. the effort to *directly* transmit their social trait) is reduced whenever they perceive their social trait to be widespread in the society. Of course, measuring this channel would require having more detailed data than Censuses' ones. As a matter of fact, I would need to observe women's (as well as their husbands') network of peers since their early life which is not possible with Census data.

Since Table 3.6 shows that foreign born immigrants' fertility choices are unambiguously explained by the most recent fertility rates in their source countries, I investigate whether their presence within MSAs has indeed an effect on the transmission of the horizontal fertility norm from foreign born to second generation women. In order to measure

[31](LaFerrara et al., 2012) show that soap operas shaped women's preferences for lower fertility rates in Brazil.

[32]In order to test whether women living closer to Europe are more likely to "be in touch" with their respective source countries, I analyzed whether the distance between the MSAs where the women in the sample lived and European capitals is correlated with the transmission of preferences, finding no significant results (regressions available upon requests).

foreign born influence over second generation women, I computed a ratio that weights their presence among the source country immigrant population of every MSA. Namely, for each source country and Census year in the data, the ratio computes how large the pool of foreign born immigrants is with respect to the one of second generation within the geographical area of residence. This variable, labeled $MigRate$, takes values between zero and one. The numerator of $MigRate$ counts, by source country and Census year, the number of childbearing age couples with at least one member being born overseas residing within the MSA. Similarly, the denominator of the ratio counts how many foreign born and second generation couples live within the same MSA over which the numerator has been computed.[33] By construction, $MigRate$ does not take into account the relative size of the immigrant population with respect to natives. The reason for this choice is linked to the result in Table 3.5 where I show that the relative size of the second generation population over the native one does not help to explain the transmission channel. An obvious caveat to bear in mind here is that I cannot control for selective migration of the women in the sample inside or outside geographical areas with more or less peers from the same *source country*. Since $MigRate$ essentially counts, for each ancestry, how many foreign born couples there are as fraction of the ancestry group itself, the variable does not point at a specific mechanism. Indeed, foreign born immigrants can act as role of models for second generation women thus increasing the incentive to behave according to a specific social norm, or, their overwhelming presence might simply increase the likelihood of a second generation woman marrying a foreign born man. While I am unable to tear these potential channel apart, all of them are consistent with the "horizontal" transmission of preferences.

In Table 3.7 I augment equation (1) interacting the newly generated variable with the

[33]The main geographical areas are MSAs, whenever a woman was not living in a MSA, I computed this figure for the smallest geographical area which were, respectively, counties (in 1910 Census), state economic areas (in 1940 and 1950 Censuses) and county groups (in 1970 Census).

current and lagged values of MFR. The first column of Table 3.7 shows that MFR_{st} is no longer significant once the interaction with $MigRate$ is added to the regression. Moreover, the interaction term's Incidence Rate Ratio is larger than the one for MFR_{st} in Table 3.3. The interaction term is not significant in the more demanding specification of column 2 where I interact Census year FEs with MSA's ones. In Table B.5 of the Appendix B.3, I perform several robustness checks where I show that the interaction of $MigRate$ with MFR_{st-30} is not significant in explaining fertility preferences. This result is consistent with the idea that the transmission of parents' norms to their daughters is not amplified in MSAs where there are many foreign born couples of childbearing age. Note that the inclusion of this interaction term has no effect on the horse race results (shown in columns (5) and (6) of Table B.5) nor any other specifications that include MFR_{st}. The significance of the lagged fertility's coefficient in the horse race specifications of columns (3) and (4) in Table 3.7 implies that there is some residual variation captured by this variable. Namely, fertility preferences of a fraction of the sample are captured by lagged fertility in their source countries.

A possible interpretation for results in the first four columns of Table 3.7 is that the marriage market matters in the transmission of social norms. Indeed, a simple way to test this would be dropping women that are married to foreign born husbands. Results of this exercise are in Columns (7) and (8) of Table 3.7, once the sample only includes women married to U.S. born husbands the vertical channel "wins" the horse race.[34]

According to (Bisin and Verdier, 2001), parents' socialization efforts to instill a specific social norm increase the smaller their own ethnic group size in the population. Namely, in the data I should find that parents' socialization effort was higher in MSAs where second generation women were less likely to socialize with foreign born peers from the same

[34]Since only one household member was asked questions about nativity in the 1940 and 1950 Censuses, I have to drop observations from these Censuses in order to be sure not to keep husband that were born abroad.

source country (i.e. where values of $MigRate$ are low). Despite the fact that I cannot directly observe parents' socialization efforts or selective migration to specific MSAs by foreign born or second generation immigrants, I estimate the horse race model of Table 3.3 dropping from the sample women living in areas where values of $MigRate$ for their respective *source countries* is equal or above 0.5. Results are shown in columns (5) and (6) of Table 3.7 and show that, in MSAs with a small share of foreign born couples in child-bearing age the vertical channel of transmission significantly explains fertility choices of second generation women. Note that a test for the equality of the estimated Incidence Rates Ratios on $MFR_{s,t}$ and $MFR_{s,t-30}$ in columns (5) and (6) rejects the hypothesis that the two are equal, bolstering the interpretation that the two variables measure different channels of preference transmission among the women in the sample.

Table 3.5: **Horse Race and presence of Second generation immigrants**

	Dependent Variable Children Ever Born					
	Current Fertility		Lagged Fertility		Horse Race	
	(1)	(2)	(3)	(4)	(5)	(6)
MFR_{st}	1.088***	1.088***			1.070*	1.070**
	(0.032)	(0.030)			(0.038)	(0.035)
MFR_{st-30}			1.069**	1.066**	1.050	1.051*
			(0.035)	(0.032)	(0.034)	(0.032)
$AncestryR * MFR_{st}$	0.853	0.982			0.857	0.990
	(0.149)	(0.173)			(0.144)	(0.172)
$AncestryR * MFR_{st-30}$			1.020	1.185		
			(0.244)	(0.211)		
Ancestry Ratio	2.537	1.797	1.508	0.921	2.481*	1.744
	(1.445)	(1.043)	(1.392)	(0.610)	(1.324)	(0.969)
Labor force status	0.775***	0.773***	0.775***	0.773***	0.775***	0.773***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
# Countries	27	27	27	27	27	27
# Observations	79090	79090	79090	79090	79090	79090
Log. Pseudolik.	-1.46e+05	-1.45e+05	-1.46e+05	-1.45e+05	-1.46e+05	-1.45e+05
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Year FE	Yes	No	Yes	No	Yes	No
MSA FE	Yes	No	Yes	No	Yes	No
MSA*Census Year FE	No	Yes	No	Yes	No	Yes

The coefficients shown are incidence rate ratios estimated from a Negative Binomial model, controls include woman's age, age squared, ten years dummies for husband's age group, sex ratio among migrants from the same source country within the MSA in which they live at the time of the Census. The sample is made of second generation married women from the 1910, 1940, 1950 and 1970 U.S. Census. * p<.1, ** p<.05, *** p<.01 S.E. in parentheses clustered at the *source country* of the parents level.

Table 3.6: **Placebo Horse Race on Foreign Born Immigrants**

	Dependent Variable Children Ever Born					
	Current Fertility		Lagged Fertility		Horse Race	
	(1)	(2)	(3)	(4)	(5)	(6)
MFR_{st}	1.146***	1.137***			1.138***	1.129***
	(0.034)	(0.031)			(0.033)	(0.030)
MFR_{st-30}			1.094	1.090*	1.064	1.062
			(0.061)	(0.053)	(0.056)	(0.048)
Labor Force Status	0.746***	0.745***	0.746***	0.745***	0.747***	0.746***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
# Countries	27	27	27	27	27	27
# Observations	35344	35344	35344	35344	35344	35344
Log. Pseudolik.	-7.92e+04	-7.81e+04	-7.83e+04	-7.82e+04	-7.83e+04	-7.81e+04
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Year FE	Yes	No	Yes	No	Yes	No
MSA FE	Yes	No	Yes	No	Yes	No
MSA*Census Year FE	No	Yes	No	Yes	No	Yes

The coefficients shown are incidence rate ratios estimated from a Negative Binomial model, controls include woman's age, age squared, ten years dummies for husband's age group, sex ratio among migrants from the same source country within the MSA in which they live at the time of the Census. The sample is made of foreign born married women from the 1910, 1940, 1950 and 1970 U.S. Census. * p<.1, ** p<.05, *** p<.01 S.E. in parentheses clustered at the country of birth level.

Table 3.7: **Mechanisms of the Two Transmission Channels**

	Dependent Variable Children Ever Born							
	Current Fertility		Horse Race		Reduced Sample		Marriage Market	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFR_{st}	1.032	1.040	1.001	1.009	1.017	1.017	1.033	1.039
	(0.029)	(0.042)	(0.033)	(0.033)	(0.018)	(0.016)	(0.023)	(0.025)
MFR_{st-30}			1.057*	1.058**	1.105***	1.104***	1.042**	1.041*
			(0.032)	(0.030)	(0.015)	(0.014)	(0.022)	(0.022)
$MigRate*MFR_{st}$	1.083**	1.082	1.107***	1.106**				
	(0.035)	(0.059)	(0.037)	(0.054)				
$MigRate*MFR_{st-30}$								
$MigRate$	0.893	0.881	0.846**	0.834*				
	(0.065)	(0.104)	(0.065)	(0.088)				
Labor force status	0.775***	0.773***	0.775***	0.773***	0.811***	0.811***	0.831***	0.828***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.009)	(0.008)	(0.006)	(0.006)
# Countries	27	27	27	27	27	27	27	27
# Observations	79090	79090	79090	79090	36628	36628	48154	48154
Log. Pseudolik.	-1.46e+05	-1.45e+05	-1.45e+05	-1.45e+05	-6.95e+04	-6.93e+04	-9.18e+04	-9.16e+04
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Year FE	Yes	×	Yes	×	Yes	×	Yes	×
MSA FE	Yes	No	Yes	No	Yes	No	Yes	No
MSA*Census Year FE	No	Yes	No	Yes	No	Yes	No	Yes

The coefficients shown are incidence rate ratios estimated using a Negative Binomial model, controls include woman's age, age squared, ten years dummies for husband's age group, sex ratio among migrants from the same source country within the MSA in which they live at the time of the Census. The sample is made of second generation married women from the 1910, 1940, 1950 and 1970 U.S. Census. In columns (5) and (6) I drop from the sample women that have a foreign born husband. In columns (7) and (8) I drop women living in MSAs with a value of $MigRate$ below 0.5. * p<.1, ** p<.05, *** p<.01 S.E. in parentheses clustered at the *source country* of the parents level.

3.6 Conclusions

The persistent effect of culture on economic outcomes has been widely documented in the economics literature. However, less attention has been devoted to how this effect can be measured and what is the mechanism underlying preferences' transmission. Previous studies have generally been silent on the channel of socialization through which second generation children picked up social traits that are displayed in their life choices.

In this paper, I analyzed observed fertility choices in a time frame in which the outcome of interest was experiencing sharp changes across countries of origin of immigrants to the U.S. The longitudinal variation in fertility norms in these countries allows me to run a horse race from which I find mixed evidence that both the "horizontal" channel as well as the "vertical" one matter in determining fertility choices of second generation women. Interestingly, I find evidence that vertical transmission acts as a substitute to the horizontal one, that is, women living in areas populated by immigrant couples from the same *source country* are more likely to adopt fertility choices similar to them. My findings are in line with the theoretical results of (Bisin and Verdier, 2001) who show that parents' socialization efforts decrease the larger their group size is in the population. These results come with some caveats: I am unable to account for women' self-selection into areas more (or less) populated by immigrants. Despite the 1910 Census lacks data on human capital accumulation, i.e. I cannot fully control for the impact of human capital on women's fertility decisions, I show robustness checks that mitigate these issues as results are virtually unchanged when I only use the Censuses for which education data is available. As measurement error in the variable measuring lagged fertility in migrants' source country might affect results, I show that they are robust using an instrumental variable approach.

More research is needed to shed light on the channel of transmission. For instance, it would be interesting to investigate the role that religion played on the horizontal vs. vertical transmission of fertility norms across the time frame considered. In addition, IPUMS linked samples might be analyzed in order to test whether self-selection into areas is an issue for the internal results of the paper.

Appendices

Appendix B

Appendices

B.1 Coale and Watkins (1986) Data

In order to compute marital fertility rates over time I used Coale and Watkins (1986) data. Namely, the authors constructed, for every country, an index (called I^f_{st}) taking values between zero and one. The index expressed how close (or far) total fertility in country s at time t was with respect to an hypothetical plateau. The plateau is constituted by the Hutterites' fertility rate. The total fertility rate index I^f_{st}, computed over all women in reproductive age (i.e. 20 to 49), is composed by the following indices:

$$\overbrace{I^f_{st}}^{\text{Total Fertility Rate Index}} = \underbrace{I^m_{st} * I^g_{st}}_{\text{Marital Fertility Rate Index of Country } s \text{ in Year } t} + (1 - I^m_{st}) * I^h_{st} \tag{A}$$

Where I^f_{st} is the ratio of the actual number of births over the hypothetical number that women would have were they to adopt the Hutterite fertility schedule. I^g_{st} is the ratio of the actual number of births occurring to married women aged twenty to forty nine years old over the hypothetical number that would be observed if the distribution of married women would adopt the Hutterite fertility schedule. Finally, I^m_{st} is a measure of the contribution of marital status to the overall rate of childbearing, this ratio is a weighted average of the proportion of married women in different age groups in the population. I^f_{st} can be written as in equation (A.1) below:

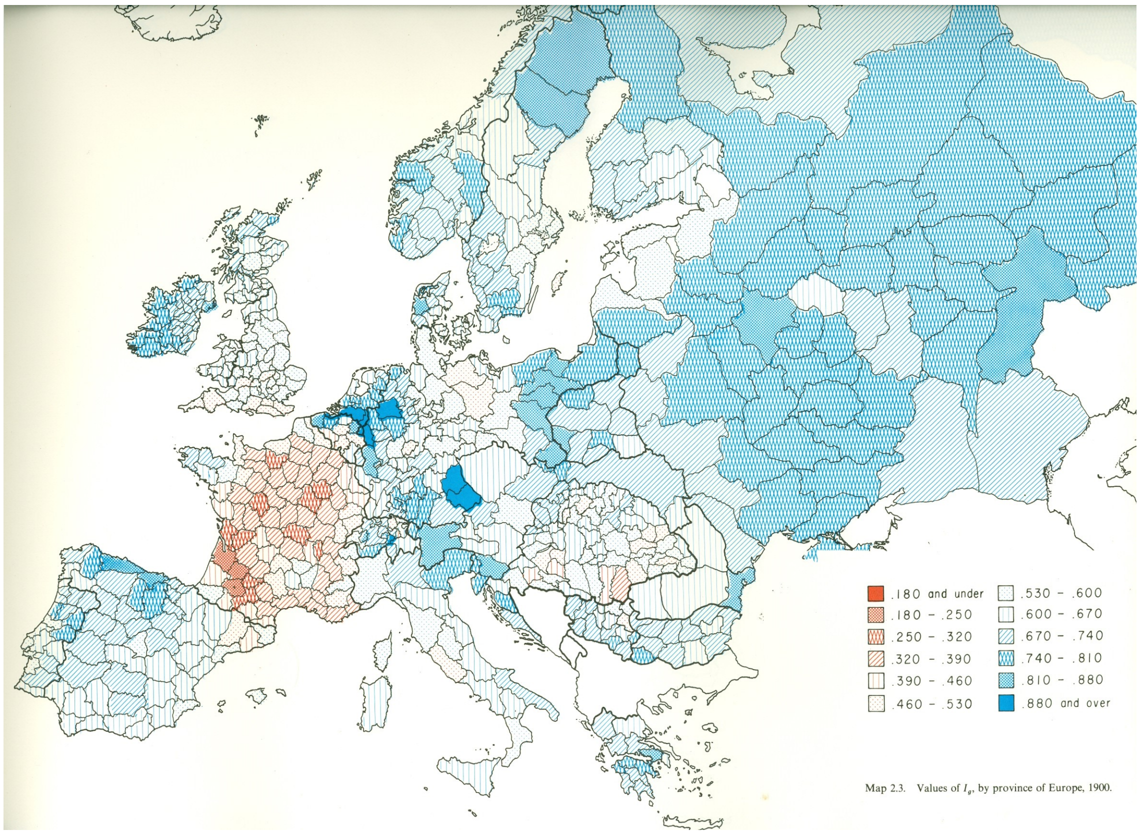
$$I^f_{ct} = \frac{B_{st}}{H^m_{st}\int_{20}^{49} h(a)w(a)_{st}\mathrm{d}a} \tag{A.1}$$

Where B_{st} is the total number of children born by every woman and $\int_{20}^{49} h(a)w(a)_{st}\mathrm{d}a$ is the plateau of maximum attainable fertility if every woman in age group $w(a)_{st}$ would follow the Hutterites' fertility schedule $h(a)$.

$$\begin{aligned}
\text{where } I^g_{st} &= \frac{B^m_{st}}{\int_{20}^{49} h(a)m(a)_{st}\mathrm{d}a} \quad I^m_{st} = \frac{\int_{20}^{49} h(a)m(a)_{st}\mathrm{d}a}{\int_{20}^{49} h(a)w(a)_{st}\mathrm{d}a} \qquad \text{(B.1)}\\
H^m_{st} &= \int_{20}^{49} h(a)m(a)_{st}\mathrm{d}a\\
B^m_{st} &= \#\text{of births occurred to married women}\\
m(a)_{st} &= \#\text{married women at age } a \text{ in country } s \text{ at time } t\\
h(a) &= \text{Hutterite's yearly fertility schedule}
\end{aligned}$$

In order to compute MFR for country s in year t the authors multiply the MFR's index ($I^m_{st} * I^g_{st}$) with the Hutterites' MFR (that is 10.94 children per woman). Since marriage market and age at marriage in European countries might differ from the one in the U.S., I^g_{st} is a variable measuring the degree to which married women restricted fertility in European countries during the time of analysis. As a matter of fact, I^g_{st} creates a "ranking" among the countries in the sample, from the ones exerting very little fertility restrictions after marriage, i.e. those with a high value of I^g_{st}, to the ones exerting high fertility restrictions during the marriage, that is those displaying low values of I^g_{st}. Figure B.1 shows the variation in I^g for many European countries in year 1900. Regions in red are those having lower values of I^g, conversely, regions with a blue scale are those that exert little fertility control after marriage.

Figure B.1: **Values of I^g_{st} when $t = 1900$ across European Regions**



Source: Coale and Watkins (1986)

B.1.1 Robustness of the Fertility Data

In order to show the validity of the data used, I run the baseline OLS regression in Fernández and Fogli (2009) and compare how results vary when substituting the epidemiological variable used by the authors with the one taken from Coale and Watkins (1986).[1]

[1] Fernández and Fogli (2009) use data from the United Nations reporting Total Fertility rates available here.

Table B.1 replicates the regression in Column 8 of Table 2 in Fernández and Fogli (2009) using the two data sources for the epidemiological variable. Namely, column two of B.1 uses the same data as the published paper while column one uses the data adopted to write this paper. Since there are only fifteen countries for which I have data from both sources I cannot replicate the regression with the same number of observations used in the original paper.[2] Despite these shortcomings and the fact that the size of the coefficient changes when compared to the results in the original paper, results are very similar when I use Coale and Watkins (1986) as a source for the MFR from the source countries. This fact is reassuring and signals that the data, at least for the period in which I have a comparable alternative source, are reliable.

[2]Moreover, Fernández and Fogli (2009) dropped the countries that signed the Warsaw Pact of 1955 which are included in this study.

Table B.1: **Baseline Regression in Fernández and Fogli (2009) using Different Data Sources**

Source of the Epidemiological Var.		(1) # of children	(2) # of children
Fernández and Fogli (2009)	TFR_{1950}		0.388***
			(0.108)
Coale and Watkins (1986)	MFR_{1950}	0.457***	
		(0.091)	
β			
	TFR_{1950}		0.1075***
	MFR_{1950}	0.1045***	
	# Countries	15	15
	# Observations	4910	4910
	MSA FE	Yes	Yes
	Adj. R-Sq.	0.043	0.042

* p<.1, ** p<.05, *** p<.01 S.E. in parentheses Clustered at the *source country* of the parents level.

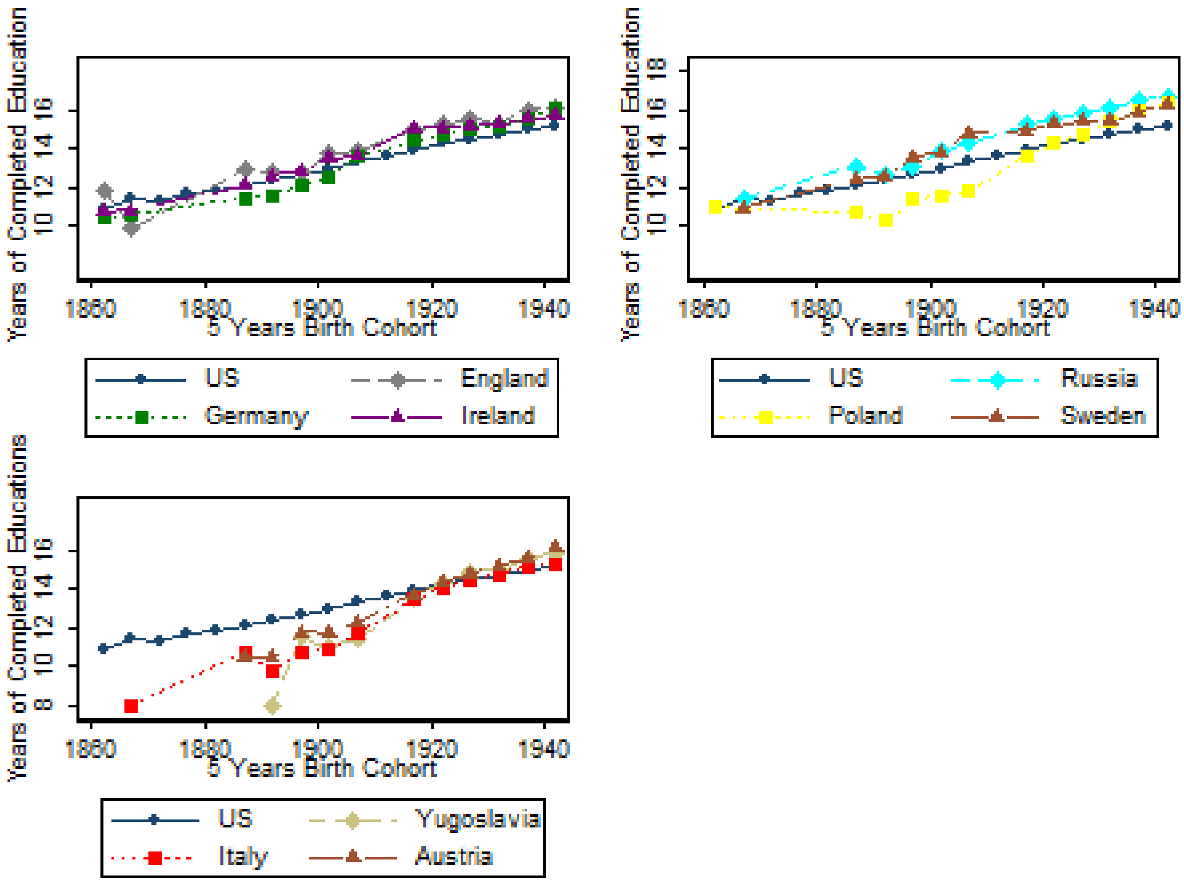
B.2 Data on Second Generation Migrants: Additional Details

Table B.2 shows the availability of the indices for various countries over time.

Table B.2: **Data Availability by Year and Country from Coale and Watkins (1986)**

Country	Year						
	1870	1880	1900	1910	1930	1940	1970
France[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Germany[4]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ireland	Yes	Yes	Yes	No	Yes	×	Yes
England[5]	Yes	Yes	Yes	Yes	Yes	No	Yes
Scotland	Yes	Yes	Yes	Yes	Yes	×	Yes
Wales	Yes	Yes	Yes	Yes	Yes	No	Yes
Italy[6]	Yes	✓	Yes	✓	Yes	✓	✓
Russia	✓	No	✓	×	✓	Yes	✓
Baltic States[7]	No	×	✓	×	✓	Yes	✓
Norway	No	Yes	✓	×	Yes	No	✓
Sweden	×	✓	Yes	No	Yes	No	✓
Finland	✓	Yes	No	Yes	No	Yes	✓
Denmark	Yes	✓	Yes	✓	Yes	No	✓
Austria	No	Yes	✓	Yes	Yes	No	Yes
Hungary	×	✓	Yes	No	Yes	No	✓
Spain	No	Yes	✓	Yes	No	Yes	✓
Portugal	No	Yes	✓	Yes	No	Yes	✓
Belgium	No	Yes	✓	Yes	No	Yes	✓
Netherlands	No	Yes	✓	Yes	✓	×	✓
Greece[8]	No	×	✓	×	✓	No	✓
Yugoslavia	No	×	No	×	✓	×	✓
Czechoslovakia[9]	No	Yes	✓	Yes	No	Yes	✓
Poland	No	No	✓	No	Yes	No	✓
Switzerland	✓	Yes	✓	Yes	No	Yes	✓
Romania[10]	No	×	✓	No	✓	×	✓

Figure B.2: **Average Education of Second Generation Married Women**



Source: Author's calculation using 1940, 1950 and 1970 Censuses.

[3]The last observation for France, Ireland, Austria, Yugoslavia, Poland, Switzerland, Hungary, Denmark, Spain, Sweden, Norway and Netherlands is in 1960.

[4]The last observation for Germany is in 1962.

[5]The last observation for England Scotland and Wales is in 1961.

[6]The last observation for Italy is in 1961, the closest observation to 1940 comes from the 1936 Census.

[7]Information about Baltic States comes from Russia's disaggregated data.

[8]The last observation for Greece is in 1961

[9]Information about Czechoslovakia before the country was established comes from Austro-Hungarian Empire's Censuses.

[10]The last observation for Romania is in 1956

Table B.3: **Distribution of Second generation immigrant women across the four Censuses**

	Census year				
	1910	1940	1950	1970	Total
Denmark	237	300	263	325	1,125
Finland	18	137	238	224	617
Norway	721	497	604	624	2,446
Sweden	533	811	859	801	3,004
England	2,690	1,050	1,095	1,370	6,205
Scotland	708	303	367	657	2,035
Wales	327	107	103	75	612
Ireland	5,199	1,262	1,338	1,539	9,338
Belgium	57	54	83	139	333
France	414	194	202	273	1,083
Netherlands	231	189	267	408	1,095
Switzerland	309	159	160	179	807
Greece	0	26	103	538	667
Italy	215	1,388	3,347	6,364	11,314
Portugal	57	94	160	345	656
Spain	30	23	64	185	302
Austria	439	448	1,007	1,048	2,942
Czechoslovakia	21	379	608	978	1,986
Germany	10,381	3,375	2,654	2,219	18,629
Hungary	44	220	486	677	1,427
Poland	0	1,111	2,312	2,816	6,239
Romania	0	57	134	187	378
Yugoslavia	0	85	222	584	891
Estonia	0	1	2	11	14
Latvia	0	6	26	27	59
Lithuania	0	143	289	343	775
Russia	130	683	1,720	1,578	4,111
Total	22,761	13,102	18,713	24,514	79,090

B.3 Robustness Checks

Table below shows results estimating a Negative Binomial model with the same covariates of (1) and three education dummies. Although the sample is different, these are the same regressions shown in columns (1), (3) and (5) of Table 3.3.

In order to test robustness of results shown in sections 3.5.1 and 3.5.3 I take two different approaches. I first estimate a Pooled OLS model rather than the Negative Binomial of equation (1). In addition, I also used I_{st}^{g} as epidemiological variable instead of MFR.Tables B.6 and B.7 replicate respectively Tables 3.3 and 3.7 of the paper using a Pooled OLS model instead. The only results the differ significantly when using this method instead of Negative Binomial are the ones in the first four columns of Table B.7. As it is evident, all the remaining results are unchanged.

Table B.4: **Horse Race Results with Education Data 1940-1970**

	Dependent Variable Children Ever Born					
	Current Fertility		Lagged Fertility		Horse Race	
	(1)	(2)	(3)	(4)	(5)	(6)
MFR_{st}	1.102***	1.106***			1.088**	1.091***
	(0.041)	(0.040)			(0.039)	(0.037)
MFR_{st-30}			1.066**	1.068**	1.055	1.056*
			(0.032)	(0.031)	(0.034)	(0.032)
LFP	0.782***	0.781***	0.782***	0.781***	0.781***	0.781***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
HighSch. Deg.	0.888***	0.890***	0.890***	0.891***	0.888***	0.890***
	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
Some College	0.962***	0.960***	0.962***	0.959***	0.962***	0.960***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
CollegeDeg.	0.881***	0.879***	0.881***	0.879***	0.883***	0.880***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
# Countries	27	27	27	27	27	27
# Observations	56329	56329	56329	56329	56329	56329
Log. Pseudolik.	-98746.357	-98589.977	-98751.955	-98596.893	-98727.149	-98570.574
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Year FE	Yes	No	Yes	No	Yes	No
MSA FE	Yes	No	Yes	No	Yes	No
MSA*Year FE	No	Yes	No	Yes	No	Yes

The coefficients shown are incidence rate ratios estimated using a Negative Binomial model. Regression controls include woman's age, age squared, ten years dummies for husband's age group, women's education dummies, sex ratio among migrants from the same source country within the MSA in which they live computed at the time of the Census and source country's GDP per capita. The sample is made of second generation married women from the 1940, 1950 and 1970 U.S. Census. * p<.1, ** p<.05, *** p<.01 S.E. in parentheses clustered at the *source country* of the parents level.

Table B.5: **Robustness Checks on Results of Table 3.7**

	Dependent Variable Children Ever Born					
	Current Fertility		Lagged Fertility		Horse Race	
	(1)	(2)	(3)	(4)	(5)	(6)
MFR_{st}	1.031	1.038			0.990	0.999
	(0.028)	(0.037)			(0.033)	(0.031)
MFR_{st-30}			1.060	1.057	1.084**	1.079***
			(0.039)	(0.042)	(0.037)	(0.031)
$MigRate * MFR_{st}$	1.067**	1.061			1.142***	1.133***
	(0.028)	(0.053)			(0.027)	(0.044)
$MigRate * MFR_{st-30}$	1.032	1.041	1.015	1.027	0.956	0.965
	(0.043)	(0.044)	(0.042)	(0.044)	(0.038)	(0.037)
MigRate	0.838	0.813	1.051	0.999	0.905	0.878
	(0.114)	(0.126)	(0.126)	(0.123)	(0.112)	(0.131)
Labor force status	0.775***	0.773***	0.775***	0.773***	0.775***	0.773***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)
# Countries	27	27	27	27	27	27
# Observations	79090	79090	79090	79090	79090	79090
Log. Pseudolik.	-1.46e+05	-1.45e+05	-1.46e+05	-1.45e+05	-1.46e+05	-1.45e+05
Country FE	Yes	✓	Yes	Yes	Yes	Yes
Census Year FE	Yes	No	Yes	No	Yes	No
MSA FE	Yes	No	Yes	No	Yes	No
MSA*Year FE	No	Yes	No	Yes	No	Yes

The coefficients shown are incidence rate ratios estimated using a Negative Binomial model. Regression controls include woman's age, age squared, ten years dummies for husband's age group, sex ratio among migrants from the same source country within the MSA in which they live at the time of the Census. The sample is made of second generation married women from the 1910, 1940, 1950 and 1970 U.S. Census. In columns (5) and (6) I drop from the sample women that have a foreign born husband. In columns (7) and (8) I drop women living in MSAs with a value of *MigRate* below 0.5. * p<.1, ** p<.05, *** p<.01 S.E. in parentheses clustered at the *source country* of the parents level.

Table B.6: **Horse Race using Pooled OLS**

	Dependent Variable Children Ever Born					
	Current Fertility		Lagged Fertility		Horse Race	
	(1)	(2)	(3)	(4)	(5)	(6)
MFR_{st}	0.194***	0.158***			0.181***	0.119**
	(0.048)	(0.040)			(0.049)	(0.046)
MFR_{st-30}			0.091*	0.143**	0.065	0.111*
			(0.047)	(0.053)	(0.052)	(0.055)
	(0.134)	(0.152)	(0.174)	(0.179)	(0.141)	(0.158)
LFP	-0.485***	-0.494***	-0.482***	-0.495***	-0.484***	-0.494***
	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)	(0.023)
β						
MFR_{st}	0.53***	0.43***			0.18***	0.12**
MFR_{st-30}			0.43*	0.14**	0.06	0.11*
# Countries	27	27	27	27	27	27
# Observations	79090	79090	79090	79090	79090	79090
Adj. R-Sq.	0.197	0.200	0.196	0.200	0.197	0.200
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Year FE	Yes	No	Yes	No	Yes	No
MSA FE	Yes	No	Yes	No	Yes	No
MSA*Year FE	No	Yes	No	Yes	No	Yes

Regression controls include woman's age, age squared, ten years dummies for husband's age group, sex ratio among migrants from the same source country within the MSA in which they live computed at the time of the Census. The sample is made of second generation married women from the 1910, 1940, 1950 and 1970 U.S. Census. * p<.1, ** p<.05, *** p<.01 S.E. in parentheses clustered at the *source country* of the parents level.

Table B.7: **Mechanisms of the Two Transmission Channels: Pooled OLS**

	Dependent Variable Children Ever Born							
	Current Fertility		Horse Race		Marriage Market		Reduced Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MFR_{st}	0.123	0.111	0.066	0.052	0.080	0.090*	0.055	0.057**
	(0.080)	(0.110)	(0.077)	(0.075)	(0.049)	(0.050)	(0.035)	(0.027)
MFR_{st-30}			0.159**	0.163**	0.132***	0.130***	0.270***	0.268***
			(0.073)	(0.068)	(0.047)	(0.046)	(0.042)	(0.040)
$MarMigRa * MFR_{st}$	0.078	0.109	0.085	0.116				
	(0.069)	(0.136)	(0.057)	(0.108)				
$MigRate$	0.039	-0.074	-0.118	-0.234				
	(0.154)	(0.289)	(0.140)	(0.226)				
Labor force status	-0.496***	-0.503***	-0.495***	-0.502***	-0.444***	-0.454***	-0.488***	-0.489***
	(0.025)	(0.025)	(0.023)	(0.023)	(0.022)	(0.022)	(0.027)	(0.026)
# Countries	27	27	27	27	27	27	27	27
# Observations	79090	79090	79090	79090	36628	36628	48154	48154
Adj. R-Sq.	0.174	0.177	0.177	0.180	0.145	0.148	0.145	0.148
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Year FE	Yes	×	Yes	×	Yes	×	Yes	×
MSA FE	Yes	No	Yes	No	Yes	No	Yes	No
MSA*Census Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Regression controls include woman's age, age squared, ten years dummies for husband's age group, sex ratio among migrants from the same source country within the MSA in which they live at the time of the Census. The sample is made of second generation married women from the 1910, 1940, 1950 and 1970 U.S. Census. In columns (5) and (6) I drop from the sample women that have a foreign born husband. In columns (7) and (8) I drop women living in MSAs with a value of $MigRate$ below 0.5. * p<.1, ** p<.05, *** p<.01 S.E. in parentheses clustered at the *source country* of the parents level.

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