patent classes for Route 128. (Casto J, Appendix A, December 2006)
17. Appendix A
18. All three biotech patent (per 1000 utility patents) distributions of the top fourteen biotech classes passed the chi-squared goodness-of-fit test at the 5% level. (Casto J, Appendix A, Dxxecember 2006)

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Jon will spend the summer after graduation in the outskirts of Delhi, India working on a social entrepreneurship project, aiming to empower rural Indians by creating greater employment opportunities through information communication technologies. Come September, Jon will find himself asking: Now what? He is open to any and all suggestions.

Ethnic Inequality and Civil War

Jonathan Phua, Stanford University

A growing literature in Political Science focuses on the relationship between ethnic economic inequality and civil war onset. Estimating the impact of ethnic inequality on civil war onset is difficult because of measurement error and lack of cross-national data. Existing studies are inconclusive and highly limited due to selection bias. Small sample sizes have significantly constrained the power of statistical tests. We use an original dataset spanning 515 ethnic groups in 99 countries to test the impact of ethnic inequality on civil war onset. We find ethnic inequality is positively related to civil war onset. However, contrary to conventional wisdom, this relationship is weak and is mitigated by other more influential factors like group size and political power.

Conventional wisdom suggests ethnic inequality predicts civil war onset. Stewart suggests that when individual self-esteem is bound up with ethnic identity, ethnic inequality produces grievances that lead to mobilization and civil war[1]. However, recent cross-national studies have been inconclusive due to methodological problems[2] (Fearon J & Laitin D, working paper presented at APSA 1999). Although case studies suggest ethnic inequality increases rebellion by disadvantaged groups, they are not generalizable and suffer from selection bias[3,4].

This paper will conduct a large-sample study of cross-national ethnic inequality. First, we review the challenges in testing the impact of ethnic inequality on civil war. Next, we attempt to overcome these challenges through a large-N statistical analysis of ethnic inequality and civil war onset. We draw on an original dataset comprising surveys conducted by the Demographic and Health Surveys (DHS) group and research conducted by Laitin, Fearon, Kasara and myself. Finally, we examine the case of the Hutu in Rwanda in order to illustrate other variables that interfere with the impact of ethnic inequality on civil war. Our results suggest that economic disadvantages weakly predict for ethnic rebellion. However, other factors like political power and group size strongly affect observed outcomes.

Theoretical Review

Political scientists have proposed both rationalist and relative deprivation explanations for civil wars (Sambanis N, presented at Brookings Institution Trade Forum 2004). Rationalist theories argue civil war is likely in states with conditions conducive to rebel organization, such as low income per capita, economic growth or mountainous terrain[5,6]. These conditions either decrease rebellion's opportunity cost or decrease the capacity of the state, facilitating the mobilization of an insurgent movement. Relative deprivation theories argue that civil wars occur when a sub-state group becomes sufficiently aggrieved to mobilize for political change.

The available evidence supports rationalist explanations for civil war (Sambanis N, presented at Brookings Institution Trade Forum 2004). However, a growing body of literature focuses on ethnic inequality, a type of relative deprivation. Stewart argues that the intersection of economic inequality and cultural differences makes culture a powerful organizing force[1]. Klugman notes that without economic inequality, group identity is likely to be weak[7]. But group inequality may have an impact on individual welfare, deepening grievances. Where the group responsible for inequality has a monopoly on political power, the aggrieved group may seek change through violence.

Empirical tests on this relationship are inconclusive and sparse. Although econometric analysis by Gurr and Moore suggests ethnic inequality increases the probability of civil war, their analysis is purely based on published reports, without rigorous empirical foundation[2]. Using the same data as Gurr and Moore, Fearon and Laitin find no relationship between inequality and civil war, citing both multicollinearity and measurement error (working paper presented at APSA 1999).

Why so few cross-national studies? Humphreys notes inequality data is unavailable for many countries (Harvard Portal on Economics and Conflict, 2002). Our research suggests these countries have vested interests in preventing data-collection. For example, Lebanon's 1926 Constitution allocates government offices using the size of each religious sect. The Lebanese government has had a powerful disincentive against collecting data that could shift this balance of power[8]. Further, these countries are often undergoing political instability that impedes data collection. If data is unavailable for countries suffering precursors to civil war, our tests will suggest the relationship between ethnic inequality and civil conflict is weaker than it is (Humphreys M, Harvard Portal on Economics and Conflict, 2002).

Another reason for the lack of cross-national studies is measurement error. Many countries face problems operationalizing definitions of their major ethnic groups. For example, heterogenous ethnic characteristics of Mestizos in Mexico make it hard to distinguish between Mestizos, Whites and Indigenous Peoples based on language or region. This makes it difficult to construct good estimates of ethnic inequality with data. Further, large-N cross-national comparisons are based on household surveys that vary in quality, reducing the likelihood that relationships between variables will be found[9]. Stewart and Klugman have proposed broader definitions of ethnic inequality that include political, economic and socio-cultural differences[1,7]. However, it is unclear if a variable will be sensitive to so wide an array of values or if it can be constructed at all.

Ethnic Inequality and Civil War

Surveys administered by the Demographic and Health Surveys (DHS) group provide a way around these problems. Using factor analysis, they assign individual wealth scores derived from responses to asset-ownership questions. This wealth score cannot be used cross-nationally as it is an ordinal ranking, not a cardinal value. We match individuals to their ethnic groups according to language or religion, following rules developed by Kasara (Kasara K, unpublished research, 2005) and based on a list of ethnic groups developed by Fearon[10]. We then compute the quintile of each individual's wealth score and aggregate by ethnic group, to find each group's mean wealth quintile on a scale of 1 to 5. This procedure creates a sample of 216 ethnic groups across 31 countries, enumerated by the *ethnic group*.

Next, we augment our DHS

quintiles with data on ethnic inequality drawn from Global Barometer Surveys, censuses and published research. Unlike the DHS data, this collection is presented across different measures, including per capita income, mean years of education, poverty incidence, and socio-economic group. We reduce concerns about data quality and cross-indicator comparisons by transforming all the data, including DHS data, into a dummy variable (*adv*) that takes the value of 1 if an ethnic group is advantaged compared to the country-mean in the best available indicator, and 0 otherwise[11]. Our sample increases to 515 ethnic groups in 97 countries. For our dependent variable, we use the Minorities At Risk (MAR) dataset, which assigns a score ranging from 0 (no rebellion) to 7 (protracted civil war) to each ethnic group for each five-year period from 1945 to 1998 based on published reports. We take the highest value across this period and code it as the maximum rebellion score *(maxreb)*. We transform *maxreb* into a dummy variable (*rebmean*) by pooling observations in the upper four and lower three *maxreb* scores to guard against misclassifications in the original rebellion coding due to lack of published reports at lower rebellion scores. An examination of cases indicates that scores of four and above fit our intuitive definition of "civil war", like the Afghan civil war or the Diola insurgency in the Casamance.

$$rebmean = \begin{cases} 1 & \text{if maxreb} \geq 4 \\ 0 & \text{if maxreb} \leq 3 \end{cases}$$

Finally, we add country-level and group-level variables from Fearon and Laitin (working paper presented at APSA 1999): GDP per capita in 1985 (*gdp85*), the proportion of a country an ethnic group comprises (*gpro*) and log of country population (*lnpop*). Descriptive statistics for the variables are shown in Table I.

Disadvantaged groups in our sample are engaged in rebellion at almost twice the rate of advantaged groups. *adv* is negatively correlated with *rebmean* at -0.1346 (N=515). Plurality groups are involved in rebellion at half the rate of minority groups, raising the possibility that the question of rebellion does not apply to them because they hold political power. However, the relationship between *adv* and *rebmean* for plurality groups (corr=-0.1981, N=97) is three times as strong as for minority groups (corr=-0.0648, N=418). Of the 12 plurality groups in our sample with positive *rebmean*, only 2 – Hutu-Twa in Rwanda and Shona in Zimbabwe – were politically dominant at the time of rebellion. This suggests that a similar causal mechanism applies to plurality groups as minority groups, and that we should retain them in our sample. A χ^2-test of *adv* on *rebmean* for all groups finds a substantively and statistically significant relationship between economic disadvantages and civil conflict (see Table II).

We illustrate this relationship by graphing the mean difference between the *maxreb* scores of advantaged and disadvantaged groups, by country. This index can take values from -7, if every disadvantaged group in the country is fighting a civil war and every advantaged group is not, to 7, if the reverse is true. The more negative the value, the stronger the correlation between economic disadvantage and civil war. If civil war onset were uncorrelated with economic status, we would expect a Normal distribution symmetric about 0 on the x-axis. The negative mean of all country means (mean = -0.57, N=99) indicates that disadvantaged groups tend to rebel more than advantaged groups. This mean rises to -1.1 (N=51) if we include only countries that have experienced civil war. Figure I highlights this relationship for all countries, Figure II illustrates the skew in the left-tail of the distribution of mean differences.

The left-skew of the distribution indicates that more disadvantaged than advantaged groups are involved in civil conflict. However, the distribution also suggests that the bivariate relationship is weak, as it approximates the superimposed Normal distribution. If the relationship were strong, we would expect a more skewed distribution.

We use Ordinary Least Squares regression to control for other variables that may impact the relationship between ethnic inequality and civil war. We use three models. The first uses *maxreb* and the second uses *rebmean* as the dependent variable. The third uses *rebmean* and omits plurality groups. We add country-dummies that take a value of 1 if an ethnic group is from a particular country and 0 otherwise. This specification controls for country and group-specific variables that affect the probability of civil war and lets us examine the relationship between inequality and civil war at the country-level[5]. The results are shown in Table III.

Model [2] detects a substantive and significant country-specific relationship between ethnic inequality and civil war, controlling for group size, country size, and country wealth. This may be a better model than model [1], as it is robust to small misclassifications of civil conflicts in *maxreb*. However, the *adv* coefficient heavily depends on the relationship between economic disadvantage and civil war *for plurality groups* (see page 5). *adv* shrinks and loses significance when plurality groups are dropped in model [3]. *gpro*'s coefficient is negative as plurality groups, which are the largest ethnic groups, tend to be economically advantaged (see page 5) and economic advantages are negatively related to civil war onset. Confirming this observation, *gpro*'s coefficient changes sign when plurality groups are dropped in model [3]. Other variables behave as expected: *gdp85* and *lnpop* have negative coefficients, in line with research suggesting that country size and per capita income have positive and negative relationships with civil war onset, respectively[5]. On the whole, our results indicate a weak relationship between ethnic inequality and civil war. But it also suggests other significant factors like *gpro* have a significant impact on civil war onset. We look to the case of Rwanda to illustrate these other factors.

Other Factors Affecting Civil Wars: Group Size and Political Power

We study two events in Rwanda's history: the 1959 riots and the 1994 genocide. Prunier observes that mean Hutu and Tutsi family incomes were virtually equal by 1959 with rising numbers of wealthy Hutu and impoverished Tutsi[12]. The ratio of Hutu to Tutsi college enrollment improved from 1/5 to 1/2 between 1932 and 1959. The income of an average Tutsi household in the 1950s was BF 4439, slightly higher than that of a Hutu household at BF 4249. The largest gap was between both Hutu and Tutsi and the Twa, whose average household income was BF 1446. These statistics make it unlikely that ethnic inequality motivated Hutu participation in the 1959 riots.

The attribution of the 1994 genocide to Tutsi subjugation of the Hutus also does not fit economic facts. DHS data from 1992 suggests no significant discrepancy between their living standards. Although the average Hutu had 3.22 years of education, while the average Tutsi had 5.21 years, 28% of Tutsi had water piped into their homes through a communal tap, while 22% of Hutu had piped water in their homes. In addition, the average Hutu lived 73 minutes from water, while the average Tutsi lived only slightly further - 86 minutes - away. It does not seem likely that ethnic inequality had a large role to play in either the 1959 riots or the 1994 genocide.

In fact, an inequality theory of civil war would predict a Twa rebellion in 1959 and 1994. The average income of a Twa family in 1959 was less than half that of a Hutu family. In 1992, a Twa lived 169 minutes from a water source and had less than 1 year of education. Yet the Twa, comprising less than 1% of Rwanda's population, remained acquiescent. This case supports our statistical model, suggesting the relationship between group size and civil war onset is stronger than the relationship between ethnic inequality and civil war.

We examine the relationship between ethnic inequality, group size, and civil war graphically by plotting the *rebmean* average at every value of *gpro*, for all disadvantaged groups (see Figure III). Although the relationship is not statistically significant, the graph's upward climb suggests at least some support for our observations above: group size does have an impact on the relationship between ethnic inequality and civil war.

Petersen's Resentment theory of ethnic conflict provides a third factor that influenced the 1959 riots: political power[13]. Resentment arises when a group believes it is in unwarranted subordination in a political ethic hierarchy; the theory predicts it will target the group furthest up the hierarchy it can subordinate through violence. This fits the evidence in 1959 Rwanda. It explains the role of the Twa: smaller, less powerful groups will not use violence, as they know it is unlikely to change the established hierarchy. Tutsis were the politically dominant ethnic group and Hutus came next, hence Tutsis were the logical target of subordinate Hutus. The withdrawal of Belgian authority also predicts for more intense violence, while the clarity of the established ethnic hierarchy predicts violence rather than cooperation. Resentment theory's emphasis on political power fits our statistical observations. Although political power is hard to statistically test, this case study suggests that economic inequality cannot outweigh the influence of political hierarchy.

Conclusion

Conventional wisdom suggests ethnic inequality affects the probability of civil war. A systematic investigation of the data confirms a weak relationship. Factors like group size and possibly political power have a greater impact on the onset of civil war. Further research should guard against problems in causation and examine ethnic inequality against other variables that may predict for civil war.

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Figures and Tables	Mean	Standard Deviation	N
I. Group characteristics			
Mean wealth quintile	3.13	.64	216
Plurality groups	3.17	.39	31
Minority groups	3.13	.68	185
Rebmean	.12	.33	515
Plurality groups	.07	.26	97
Minority groups	.13	.33	418
Advantaged groups	.08	.28	232
Disadvantaged groups	.15	.36	283
Adv	.45	.50	515
Plurality groups	.63	.49	97
Minority groups	.41	.49	418
Gpro	.18	.24	515
Advantaged groups	.24	.29	232
Disadvantaged groups	.17	.24	283
II. Country Characteristics			
GDP per capita in 1985	3419.82	4251.21	444
Population	44935.71	127582	444

Table 1. Descriptive Statistics.

rebmean	adv		Total
	Disadv	Adv	
No Rebel	241	212	453
	85.16	91.38	87.96
Rebel	42	20	62
	14.84	8.62	12.04
Total	280	235	515
	100.00	100.00	100.00

Table 2. χ^2 test of adv against rebmean. Pearson chi2(1) = 4.6582 Pr = 0.031

	[1]	[2]	[3]
Depvar	*maxreb*	*rebmean*	*rebmean*
adv	-.27	-.05*	-.01
	(.19)	(.028)	(.035)
gdp85	-.00014	-.000038**	-.000072**
	(.00011)	(.000016)	(.000022)
lnpop	.16	.06	.13**
	(.29)	(.044)	(.063)
gpro	-.79*	-.14**	.29
	(.43)	(.066)	(.24)
constant	1.87	-.048	-.42
	(2.81)	(.44)	(.61)
N	444	444	364

Table 3. OLS Regression Results. Country-dummy coefficients omitted. Standard errors in parentheses. *p<0.10 **p<0.05

Jonathan Phua is a junior from Singapore majoring in Political Science and Management Science & Engineering. He first encountered the project on Ethnicity, Insurgency and Civil War in David Laitin's freshman seminar, and has been fascinated by ethnicity and conflict ever since. He thinks undergraduate research is a key part of the Stanford experience, and he thanks Professors David Laitin and James Fearon for their invaluable guidance and advice. He enjoys thinking about complex problems, reading and criticizing poetry, watching plays and traveling all over the world.

The Genetic Engineering of America's Farmland: Concerns regarding patentability and the use of intellectual property rights

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An inducement to create

The extent of patent law's reach has long been a subject of interpretation and debate. In authoring the 1793 Patent Act, Thomas Jefferson viewed the patent monopoly not as a natural right, but as "an inducement to bring forth new knowledge."[1] Science, he believed, was the most certain way to further societal progress.

Over the years, courts have broadly interpreted the patent statute, granting ownership over innovations once ineligible for protection. As intended by the framers of the original Act, expansion of the scope of patentability has nurtured the development of scientific spheres like biotechnology, but it has also allowed companies to exert a historically unprecedented amount of control within their industries. In recent cases involving biotech giant Monsanto Corporation, U.S. courts have consistently supported Monsanto's patents on genetically modified seeds, holding farmers liable for infringement beyond their control.

This raises two questions: first, is it ethical to assign monopoly over a living thing, especially one as fundamental as seed? And second, how far does that right extend? Perhaps there is a line, as Jefferson proposed, where we must separate legitimate protection from abuse.

Public tradition becomes private practice

In millennia past, seed breeding was not an exact science. Farmers selected and crossed the best-adapted varieties, building upon previous knowledge through experimentation. The trend toward science-based solutions spread to the U.S. from Europe in the 18th century, and as the economy grew increasingly dependent upon agricultural exports, the need for production uniformity and higher yields moved seed breeding from farms to centralized public research centers like universities.[2] Today, however, particularly in lucrative areas like commercial crop breeding and biotechnological applications, private agricultural research has — and continues to — displace public research. In 1995, private investment constituted more than half of the $20 billion spent on agricultural R&D in the developed world.[3] The major catalyst for this change has been the extension of intellectual property rights to biotechnologies, which has made investments in such projects more lucrative and thus appealing to companies seeking to maximize profits.[4] Although universities still play a role in the research process, their sources of funding too have shifted from being almost entirely public, to largely private, in nature.

Although agricultural technologies like machinery and chemicals have always been protected under the Patent Act, similar patent protections had never been extended to plants on the basis that they were creations of nature, which are not patentable. In 1930, Congress passed the Plant Patent Act (PPA), which permits the patenting of plants, but only those that reproduce *asexually*.[5] Congress had aimed to limit the reach of PPA, but conceding in 1970 that sexually reproducing plants needed some form of protection as well, passed the Plant Variety Protection Act (PVPA), which grants owners an exclusive right to multiply and market varieties of the protected seed for 20 years.[6] Though similar in nature to utility patents (a generic patent category for inventions that perform useful functions), PVPA made two critical exceptions: scientists could use PVPA-protected varieties for research, and farmers would be able to save patented seed for the next harvest.

The biggest change came in 1980, when the U.S. Supreme Court ruled in *Diamond v. Chakrabarty* that a living microorganism could be patented under the utility patent criteria for regular inventions.[7] The U.S. Patent and Trademark Office (U.S. PTO) affirmed and extended this new rule in *Ex parte Hibberd* (1985), which concluded that all sexually reproducing plants were eligible for utility patent protection.[8] Following the ruling, the U.S. PTO began accepting applications for utility patents on sexually reproducing plants, even though Congress had never authorized the agency to do so.[9] With these revolutionary reinterpretations of the law, biotechnology became a highly attractive and lucrative industry, almost overnight.

Utility patents v. PVPA

Some university researchers believe that the encompassing of genetically engineered[10] (GE) plants within the meaning of 35 U.S.C. § 101 — the section of the Constitution that enumerates criteria for patentability — is a beneficial change, since it has enabled companies to recoup their research costs, which can easily reach into the tens of millions for the requisite lab research, field testing, maintenance research, and commercialization steps. Without the potential for financial returns, private firms would have no incentive to pursue expensive biotech projects.[11]

Farmers, lawyers and policymakers tend to be less enthusiastic about the changes regarding plant patentability because the statutory exemptions that exist under PVPA do not apply to utility patents. In other words, patent holders can legally exclude use of the patented variety, even for research or agricultural purposes. One of the most controversial outcomes has been the use of this restriction by biotech companies to bar farmers from farming their land in the traditional manner. In fact, Monsanto's "Technology Use Agreement," which farmers must sign in order to use Monsanto's GE seed varieties, *prohibits* farmers from saving seed and replanting it the following season. [12] Instead, farmers must purchase a new supply each year, a highly inefficient practice given that the perfectly acceptable seed from the first crop goes to waste. Those who fail to comply with the agreement terms — whether out of ignorance, negligence or no fault of their own — face serious financial consequences. This controversial agreement has been the basis for Monsanto's suits against numerous U.S. farmers.

Agricultural law expert Dr. Roger McEowen predicts that the new utility patent rulings on plants will accelerate the movement of germplasm[13] ownership from the public to the private domain.[14] Monsanto already owns 647 biotech plant patents — far more than anyone in the market[15] — and the industry-wide total is only poised