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Why do some poor countries see armed conflict while others do not? A dual sector approach

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ABSTRACT

Low level of GDP per capita is a robust and widely applied predictor of civil war. Yet, GDP is a crude macro-level indicator that masks considerable heterogeneity in economic structures, and it is less well able to explain variation in conflict risk among low-income countries. Here, we consider the merit of classic dual sector theory in improving common economic models of civil war. Two basic expectations are derived: the relative size of the traditional sector increases conflict risk via low opportunity cost and high share of immobile wealth, whereas high relative labor productivity (RLP) in the modern sector compared to the traditional sector facilitates labor mobility and wage growth, thus reducing the viability of rebellion. We evaluate these expectations via out-of-sample prediction analysis of civil conflict involvement, drawing on a unique 10-sector dataset of economic activity among 40 countries across the world since 1969. The analysis provides robust evidence that poor countries with a comparatively productive modern sector are less conflict prone than countries at similar income levels with lower RLP ratios. However, further probing into potential mechanisms producing this relationship does not provide decisive evidence in favor of any potential mechanism. We conclude that replacing GDP per capita with indicators of sector size and relative productivity improves the predictive performance of common civil war models, although more research is needed to assess the generalizability of these findings and to gain further insight into the underlying causal pathways linking relative labor productivity with reduced conflict risk.

1. Introduction

Per capita income is commonly found to be an important predictor of civil war (Colaresi & Mahmood, 2017; Hegre & Sambanis, 2006; Muchlinski et al., 2016). Several conflict theories build on this observed relationship, arguing that aspects of underdevelopment, such as low opportunity cost of conflict participation or low state counterinsurgency capacity, drive the result (Blattman & Miguel, 2010; Collier & Hoeffler, 2004; Fearon & Laitin, 2003). Yet, the robust negative effect of GDP per capita on civil conflict involvement is weaker among developing countries and belies the fact that many low-income countries remain peaceful.

This study seeks to shed new light on the development–civil war relationship by introducing three notable innovations. First, observing that aggregate GDP statistics disguise considerable heterogeneity in the configuration of national economies, we suggest that economic models of civil war can benefit from incorporating information on economic structures and transformation processes. Informed by classic dual sector theory (Lewis, 1954), we disaggregate GDP per capita and consider how sector size and labor productivity shape conflict risk. All else equal, we expect a larger traditional sector to increase conflict risk, due to low opportunity cost of rebellion and a high share of immobile wealth that can be appropriated through violent means. Conversely, high relative labor productivity (RLP) gap between the traditional and modern sector may decrease conflict risk through wage growth and structural transformation that reduce the viability of rebellion.

Second, we evaluate these corollaries by exploiting unique multi-sector economic data provided by the Groningen Growth and Development Centre (Timmer et al., 2015). The GGDC 10-Sector Database contains statistics on labor size and value added for 10 distinct economic sectors for 40 countries worldwide over the past half century. Unlike other catalogues of cross-national economic data, the GGDC data incorporates consistent estimates of informal economic activities, which constitute a central part of the traditional sector and are central to this analysis.

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Third, acknowledging that economic performance, structural transformation, and armed conflict are inherently endogenous, we depart from conventional regression-based hypothesis testing and instead rely on a rigorous cross-validation framework. In doing so, we are able to assess whether indicators of sector size and relative productivity are substantively relevant for understanding conflict risk and improve on our ability to predict civil conflict out of sample, compared to a benchmark GDP per capita model. Out-of-sample prediction is especially useful in this case since predictive accuracy is an impartial criterion by which to evaluate a model against alternative specifications (Cranmer & Desmarais, 2017; Ward et al., 2010).

In line with expectations, we find that models accounting for sector size and RLP predict civil conflict significantly better than the conventional GDP per capita model. In particular, countries with a small but productive modern sector enjoy a much lower average conflict risk than other countries at similar income levels with lower RLP scores. We then proceed to evaluate the potential drivers of this finding. According to the dual sector model, high RLP is indicative of high labor mobility, leading to growth in real wages and expansion of the modern sector, such that participation in violence becomes relatively less attractive. However, labor mobility in developing countries often face significant barriers, and we find limited evidence that high RLP is associated with growth in modern sector employment. An alternative interpretation would be that high RLP signals high rent-seeking potential and relatively high counter-insurgency capability by the state. However, RLP correlates weakly with common proxies for military and bureaucratic state capacity. Instead, we tentatively interpret this result in line with resource mobilization theory, where a small but wealthy urban elite, favored by the status quo, provides stability by denying support to aspiring but less capable rural challengers.

We conclude that replacing GDP per capita with sector-specific size and productivity statistics improves our ability to predict future civil conflict, although better data are needed to delve deeper into the mechanisms driving this association, as well as evaluating the generalizability of the results beyond the sample determined by the GGDC data.

2. Theoretical framework

A fundamental premise of economic models of civil war is that conflict risk increases when the perceived value of violent appropriation increases relative to the cost. The relative returns from violent appropriation are determined by the nature and prevalence of wealth in society and the availability of outside options. In general, societies with predominantly immobile wealth that can be captured through territorial control are considered more prone to violent contestation (Boix, 2008), especially if the territory contains valuable resources that easily can be extracted (e.g., alluvial gems and opium poppy) or taxed (e.g., petroleum and precious minerals) (Le Billon, 2001). At the same time, the viability of rebellion also depends on the cost of labor, determined by regular employment opportunities and the level of real wages in society.

Since the availability of lootable wealth and prevalence of poverty both correlate (negatively) with level of economic development, these processes are often represented by GDP per capita in empirical models of civil war. However, GDP per capita is also frequently proxying for alternative causal explanations, including arguments linking higher country-level income to increased monitoring and counter-insurgency capabilities (Fearon & Laitin, 2003) or a market-capitalist economy increasing incentives for rule of law and peaceful conflict resolution (Mousseau, 2012). A second limitation with GDP per capita as a catch-all indicator of economic development is its inability to differentiate between macro-level appropriation dynamics, individual opportunity cost, and grievance-based explanations (Nelson, 2019). Third, the widely accepted negative statistical association between GDP per capita and civil war is driven mostly by a large group of wealthy and internally peaceful states. GDP per capita is less well able to explain variation in conflict propensity among developing countries, and the strong negative average effect hides the fact that many low-income countries also have long traditions for peaceful conflict resolution.

One source of heterogeneity among low-income countries originates in the fact that development evolves as a transformation of employment opportunities and economic structures in society (Kuznets, 1966; Lin, 2012; Rostow, 1971; Schumpeter, 1911). Could it be that the notion of structural transformation provides insights also into the ubiquitous GDP–civil war relationship? In the following sections, we outline a simple economic model of civil conflict, inspired by the dual sector model (Bourguignon & Morrisson, 1998; Gollin, 2014; Lewis, 1954; Temple, 2005; Wang & Piesse, 2013), where we consider how the size of the traditional sector and structural transformation marked by high productivity gap between the traditional and modern economic sectors influence conflict risk.

To be clear, this is not the first study that seeks to incorporate elements of dual economies and structural transformation into the study of civil war. Much of the older literature on peasant rebellion and revolutions is explicitly framed around unjust economic structures and deep socioeconomic cleavages as sources of popular resistance (e.g., Goldstone, 1991; Scott, 1976). More recent contributions highlight the role of modernization in contemporary social movements (e.g., Butcher & Svensson, 2016; Della Porta, 2015). Perhaps most immediately relevant to this study, Chatagnier and Castelli (2019) explore the relationship between modernization and civil war onset using a three-sector approach. However, where that study focuses on how conflict risk patterns change as countries modernize and experience a post-materialist value shift, ours seeks to add insight into apparent heterogeneity in conflict risk among countries in earlier stages of development by incorporating elements from dual sector theory.

2.1. Traditional sector size and civil conflict risk

In developing countries, most of the workforce is employed in the traditional sector. The traditional sector is often equated with subsistence agriculture, although labor-intensive services and whole-sale trade also can be considered part of this sector (Lavopa & Szirmai, 2018; Rodrik, 2018). A fundamental feature of these activities is that they comprise surplus labor, where real wages are higher than the marginal product of labor (Wang & Piesse, 2013). Since real wages are low, the opportunity cost of foregoing normal economic activity and participating in violence also tends to be lower than in more developed economies (Collier & Hoeffler, 2004). A second central feature of developing countries is that much of the wealth is tied to land. Since land is an immobile asset, it can be captured, controlled, and exploited by armed force relatively easily, especially if the central state is weak. Developed economies, in contrast, comprise mobile wealth that is conducive to capital flight in the face of threat, lowering the viability of violent appropriation (Boix, 2008; Hirschman, 1978). Moreover, economies dependent on primary commodity production such as agriculture tend to have less developed internal trade networks than other countries (Humphreys, 2005). In line with the notion of a liberal peace, trade and other forms of interaction facilitate greater levels of social cohesion and economic interdependence between regions and actors, thereby reducing the risk of armed conflict (Hegre et al., 2010). These observations give rise

to the following basic expectation: *Civil conflict risk is positively associated with the size of the traditional sector, all else equal.*

2.2. Relative labor productivity and conflict risk

Economic development involves the movement of labor from the traditional sector into the modern economy (Kuznets, 1966; Lewis, 1954). Indeed, the structural transformation from labor-intensive agriculture and petty services to more productive activities, such as manufacture and finance, has featured centrally in the development of all wealthy countries in the world today. To better understand this development process, it is instructive to consult Lewis' (1954) classic dual economy model, pitting a traditional agricultural subsistence sector against a modern industrial sector.

A key feature of the dual sector model is that real wages in the modern sector are equal to or lower than the marginal productivity of labor, whereas real wages in the traditional sector are often higher than the marginal productivity due to diminishing returns and surplus labor (Lewis, 1954; Wang & Piesse, 2013). In such an economy, labor can be transferred out of the traditional sector without lowering the output. Migration into the modern sector will result in growth in real wages in the traditional sector, since output per remaining agricultural worker increases (Bourguignon & Morrisson, 1998; Temple, 2005; Vollrath, 2009). High relative labor productivity (RLP) in the modern sector compared to the traditional sector signals employment opportunities for underemployed agricultural workers (Harris & Todaro, 1970). High RLP thus facilitates a process of structural change that results in wage growth in both the traditional sector (because surplus labor is removed) and the modern sector (because of high demand for additional labor), thereby raising the opportunity cost of participation in violence (Collier & Hoeffler, 2004).[1] Simultaneously, structural change decreases the dominance of immobile assets, diminishing the appeal of violent appropriation (Boix, 2008; Hirschman, 1978).

This process of structural change, where high RLP leads to growth in real wages, assumes no friction in labor migration between the traditional and the modern sector. In reality, there may be significant barriers, for example due to scarcity of required skills (education, language, etc.), physical or cultural challenges, or domestic policies in force that curb labor mobility. For example, many autocracies execute tight regulations on labor mobility that favor the urban elite (Banerji & Ghanem, 1997; Shifa, 2013). Where barriers to entry into the modern sector are present, RLP no longer proxies real wages in the traditional sector. Instead, high RLP would be indicative of high inequality in productivity and income between a wealthy urban class and a large, marginalized rural economy (Wang & Piesse, 2013, p. 89). Such structural productivity imbalance might also reduce conflict risk. On the one hand, high wealth generation in the modern sector increases state revenues and facilitates improved regime coercive and co-optive capacities (Fearon & Laitin, 2003; Fjelde & De Soysa, 2009). States with strong military and bureaucratic capacities are generally considered better able to monitor their population and remove aspiring challengers before conflict breaks out (Holtermann, 2012; Sobek, 2010). On the other hand, a small but privileged urban class profiting from modern sector revenues have few incentives to change the status quo and may resist calls from the marginalized masses to rise up against injustice in protection of their own position (Svolik, 2012; Hellmeier & Weidmann, 2020). Autocracies with high levels of corruption have been shown to be less prone to regime change than their less corrupt peers (Fjelde & Hegre, 2014), which again reflects selective distribution of power and resources on expense of the poor. The rural poor, in contrast, typically possess limited skills and resources to mobilize a potentially violent opposition on their own, and without the assistance of elite actors the likelihood of success is small (McCarthy & Zald, 1977; Tilly, 1978).

Although the storylines linking high relative labor productivity with societal development under barriers to labor migration are qualitatively different from the wage determination mechanism, the observational implication for conflict risk is similar: *RLP is inversely related to conflict risk, all else equal.*

3. Materials and methods

To evaluate the two theoretical propositions, we construct a panel dataset with annual observations of 40 countries for the period 1969–2012. The sample of countries and the temporal range are determined by the availability of the economic sector data, see below. As shown in Fig. 1, the sample represents a reasonable geographical spread, mixing developed and developing countries from across the Americas, Western Europe, Africa, and Asia. The average civil conflict rate in our dataset (0.19) compares well with the global average for the same period (0.15), and the distributions of GDP per capita and education levels also are comparable. However, our sample is notably more democratic than the global average (0.43 versus 0.32 on the V-Dem Liberal Democracy Index), tends to be more populous than the global average, and the absence of former Soviet republics and countries in the Middle East region is conspicuous. For this reason, caution should be exercised whenever drawing general conclusions from our analysis.

3.1. Civil conflict

The main dependent variable is a binary civil *conflict incidence* indicator, taken from the UCDP/PRIO Armed Conflict dataset v.20.1 (Gleditsch et al., 2002; Pettersson & Öberg, 2020). Armed civil conflict is here defined as fighting over territory or governmental power between a state and one or more non-state challengers that results in at least 25 battle-deaths in a calendar year. In Supplementary Material, Section S3, we document tests of *conflict onset*, defined as the first year of conflict as well as the first year of renewed fighting after at least one inactive year.

3.2. Sector size and relative labor productivity

The economic data is provided by the Groningen Growth and Development Centre's GGDC 10-Sector Database (Timmer et al., 2015), which contains sector-specific employment figures [*emp*] and value-added estimates [*vaq05*] in constant 2005 local currency for ten economic sectors for 40 countries.[2] Although the original data extends back to 1950 for some countries, coverage in the early period is poor, so our dataset begins in 1969.[3]

[1] A critique of the wage determination mechanism embedded in the classical notion of structural transformation, commonly known as Baumol's cost disease, refers to the fact that as economies develop, salaries tend to rise also in jobs with little or no productivity gains due to reallocation of resources. However, in countries in early stages of development – the primary concern of this study – where the traditional sector remains large and surplus labor is rampant, this dynamic does not play out.

[2] The ten sectors, which are based on the International Standard Industrial Classification ISIC rev. 3.1., are: agriculture (including hunting, forestry, and fishing) [*agr*], mining [*mng*], manufacturing [*man*], public utilities [*pu*], construction [*con*], trade services (wholesale and retail; repair of motor vehicles, motorcycles, and personal and household goods; hotels and restaurants) [*wrt*], transport services [*tra*], business services [*fire*], government services [*gov*], and personal services (community and personal activities) [*oth*].

[3] Results do not change substantively if all available observations in the GGDC dataset are included in the analysis. However, since we lack estimates for many country-years in the 1950s and 1960s, extending the time series would result in a dramatic increase in the variation in N among the training and test sets, obstructing direct comparisons and resulting in less stable estimates for early years. Using 1969 as start year and 20-year training periods permits beginning the out-of-sample cross validation in 1990.

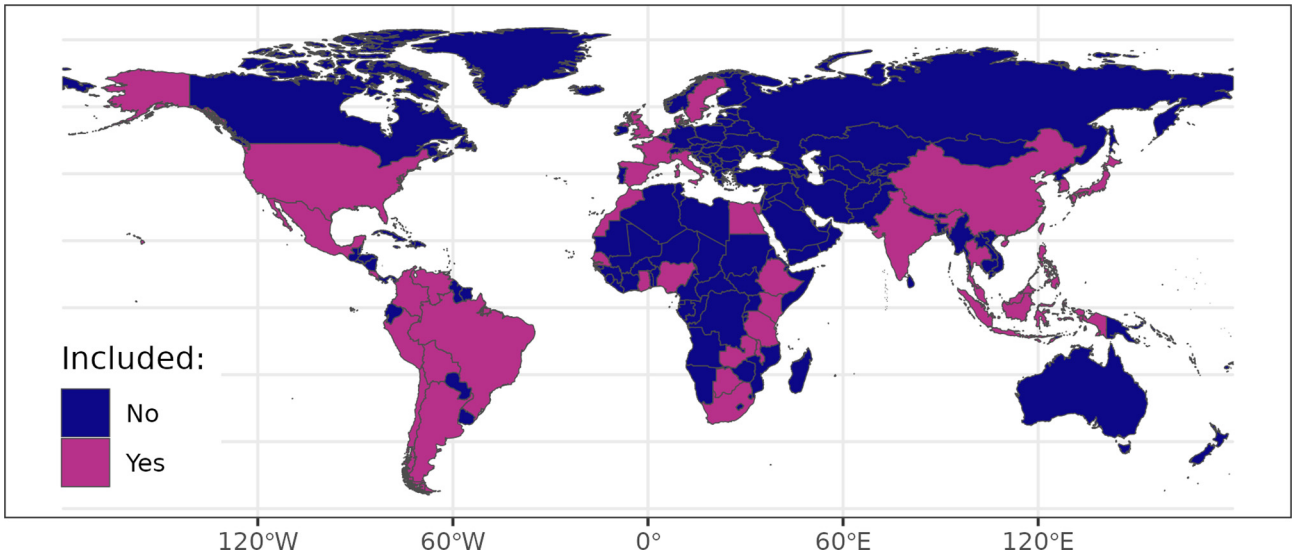

Fig. 1. Countries included in the analysis.

The limited spatial domain of the GGDC data might seem like a severe restriction. Even so, this data is superior to all available alternatives and uniquely enables empirical testing of the propositions developed in this study. For instance, while the World Development Indicators (World Bank, 2020) also provide information on labor size and value added of the agricultural sector, estimates are only available for the post-1990 period and classification schemes and measurement quality are inconsistent across countries, limiting cross-country comparisons.[4] Perhaps the most important weakness is the highly varied treatment of non-wage labor and other informal economic activities that are inherent to traditional economies. The GGDC 10-Sector Database has been compiled especially with these issues in mind, drawing on a broad set of sources to estimate value added from smaller firms, self-employed, and unpaid family members, as well as ensuring intertemporal, international, and internal consistency in the time-series.

We define the traditional, labor-intensive sector as comprising agriculture [*agr*] and trade services [*wrt*] whereas the modern, capital-intensive sector consists of all other activities except mining, which is preserved as a separate predictor due to its exceptional level of productivity and known association with conflict risk (e.g., Ross, 2015).[5] Although it is common to proxy the traditional sector with agriculture only, wholesale and retail trade in developing economies often share fundamental features with agriculture, notably extensive underemployment (i.e., surplus labor) and zero or negative marginal product of labor. Partly for this reason, *wrt* is sometimes described as the urban 'murky sector' (Fields, 1975, p. 172). Importantly, many workers in contemporary developing countries who move out of agriculture are absorbed directly into *wrt*, having little impact on the sector's overall productivity, labor supply or asset mobility (Atolia et al., 2020; Enache et al., 2016; McMillan et al., 2014; Rodrik, 2018). Such a transformation does not affect the economic structure in a way that is relevant for the economic model of conflict. Similar definitions of the traditional sector can be found in previous literature (e.g. Lavopa & Szirmai, 2018).

We calculate the relative size of the traditional sector, *a*, as the share of the total workforce employed in the sector:

$$a_{\text{trad}} = (emp_{\text{agr}} + emp_{\text{wrt}})/emp_{\text{total}}.$$

As a measure of sector importance, we calculate the traditional sector's share of value added, *s*, expressed in a similar manner:

$$S_{\text{trad}} = (vaq05_{\text{agr}} + vaq05_{\text{wrt}})/vaq05_{\text{total}}.$$

Relative labor productivity (RLP), or the ratio of the average product of labor in the traditional and modern sectors, is then given as

$$\widehat{RLP} = \frac{1 - s_{trad}}{s_{trad}} \frac{a_{trad}}{1 - a_{trad}}.$$

$\widehat{RLP}$, our operationalization of RLP,[6] is higher when the traditional sector employs a large share of the total labor force and the value added of the traditional sector is small, relative to total value added in the economy. As countries develop, the traditional sector shrinks, leading to a diminishing level of $\widehat{RLP}$ regardless of the actual productivity gap between the economic sectors. For that reason, $\widehat{RLP}$ only captures our theoretical construct when a_{trad} is sufficiently large (i.e., in a dual economy). It makes sense, therefore, to model the effect of RLP through an interaction with a_{trad}.

Estimates of GDP per capita are obtained from Penn World Table 9.1 (Feenstra et al., 2015). We use expenditure-side real GDP at chained purchasing power parity and take the natural logarithm of the per capita indicator to account for a non-linear association with civil conflict risk.

Fig. 2 provides a visual presentation of the association between traditional sector size, RLP, and GDP per capita. As revealed in panel A, RLP varies considerably among low-income countries as not all economies comprise productive, capital-intensive businesses. Likewise, we find that the spread in RLP ratios are much greater when the traditional sector is large (panel B). Panel C suggests that per capita income is strongly (but not perfectly) negatively related to the size of the traditional sector. Overall, countries with high RLP seem to be less affected by conflict.

3.3. Prediction framework and model specifications

The relationships we investigate involve inert and partly endogenous processes. Since causal effects are difficult to attribute

[4] See Supplementary Material for further details on the data sample and alternative tests using global data derived from the World Development Indicators (World Bank, 2020).

[5] See Supplementary Material for details on the measurements and for results based on an alternative operationalizations of the traditional sector.

[6] We do not use RLP and $\widehat{RLP}$ consistently across figures, variable names, and in the Supplementary Materials but we point out the difference in the main text.

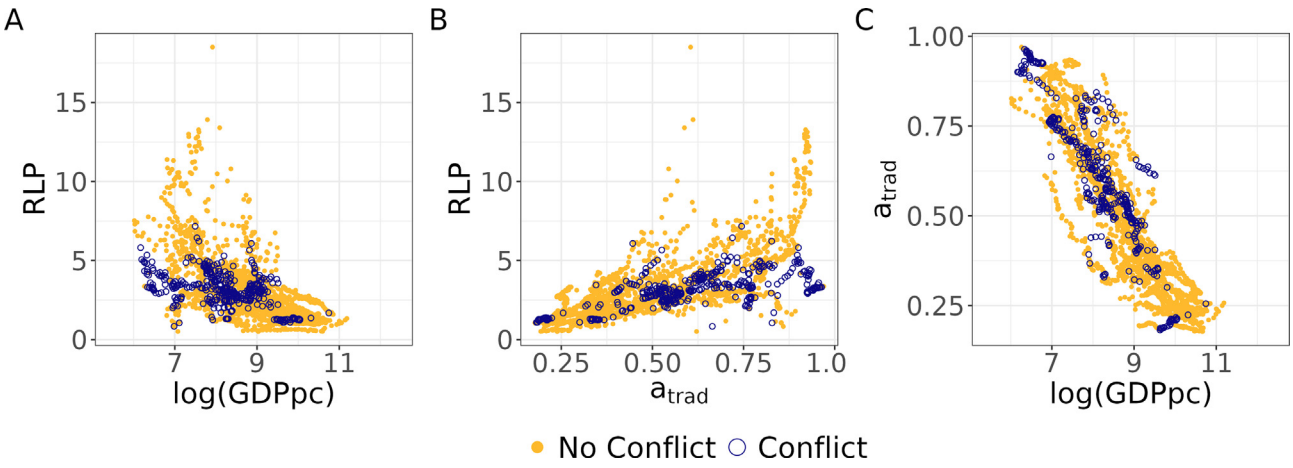

Fig. 2. Bivariate scatter plots of key variables. Country observations with vs. without civil conflict as a function of (A) log GDP per capita and RLP, (B) share employed in the traditional sector and RLP, and (C) log GDP per capita and share employed in the traditional sector.

and isolate in endogenous systems, we prefer predictive modeling over conventional null hypothesis testing. Out-of-sample prediction is especially useful in this case since predictive accuracy is an impartial criterion by which to evaluate a model against alternative specifications (Cranmer & Desmarais, 2017; Ward et al., 2010). To evaluate the relative performance of competing economic models, we perform leave-future-out cross-validation (LFO-CV), estimating models on 20-year sliding windows (from 1969 to 89 until 1989–2009) and predicting on the next 3 years (from 1990 to 92 until 2010–12), resulting in a total of 21 alternative partitions in training and test datasets for model evaluation.[7] Modeled relationships and predictive performance that are relatively stable over time are taken to indicate stronger and more robust causal relationships, compared to when parameters vary across cross-validation sets.

The prediction analysis considers five economic models of civil conflict that are estimated using both generalized linear models (GLM) and more flexible generalized additive models (GAM) with non-linear spline functions. As shown in Table 1, the baseline model (GLM1) includes log GDP per capita and a common set of controls: growth in GDP per capita ($\Delta GDPpc$), log population, and share of the total workforce employed in mining and extractive industries (a_{mng}). These variables have consistently been found to be good predictors of civil conflict (Colaresi & Mahmood, 2017; Hegre, 2014; Hegre & Sambanis, 2006; Muchlinski et al., 2016). The population estimates are obtained from Penn World Table 9.1 (Feenstra et al., 2015) whereas the mining variable is derived from the GGDC data. The baseline model is then benchmarked against a set of models that replace GDP per capita with measures of a_{trad} and $\widehat{RLP}$ in increasingly complex ways (GLM2–4), as well models replacing growth in GDP per capita with growth in value added per employed in the respective economic sectors (GLM5). Similar models are created using a non-linear GAM modeling approach. The GAM models allow us to capture associations that fit better with the empirical data than linear models allow for, at the risk of overfitting to particularities in the training data that do not carry over to future data (Hastie et al., 2009). In the GAM models, we explore both independent splines (GAM1–3), as well as interactive anisotropic splines (full tensor products; GAM 4–5).

We evaluate the performance of the models by measuring area under the precision-recall curve (AUC-PR), given by precision $\equiv$ TP/(TP + FP) and recall $\equiv$ TP/(TP + FN), where TP = true positive, FP = false positive, and FN = false negative prediction. Since we are predicting a relatively rare event where the main interest is on positive outcomes, we give precedence to the performance on PR over the receiver operating characteristic ROC, although both metrics are reported in Supplementary Materials.

4. Results and discussion

Fig. 3 visualizes the main results in terms of models' predictive performance and the behavior of key economic variables. Across the evaluation sets we note three general patterns. First, models including $\widehat{RLP}$ and traditional sector size tend to perform better than the benchmarking *GDPpc* models (GLM1/GAM1), demonstrating the former specification's superior ability to separate between peaceful and conflict-affected country years. Second, the best GAM models vastly outperform the best GLM models. Third, the models' overall predictive power is higher in later time periods.

Specifically, Fig. 3A reveals that simply replacing *GDPpc* with a_{trad} returns similar predictions when using the linear specification (GLM1 vs. GLM2), but significantly improves the performance when relying on a non-linear model (GAM1 vs. GAM2). Adding $\widehat{RLP}$ as an additive term (GLM3/GAM3) and including it in interaction with a_{trad} (GLM4/GAM4) provide further improvements in predictive performance. The average AUC-PR score of the best dual sector model (GAM4; AUC-PR = 0.67) is as much as 14 percentage points higher than the best GDP per capita model (GLM1; AUC-PR = 0.53) across the cross-validation sets.

The coefficient estimates from the linear models (Fig. 3B) reveal effects in the expected direction and most are statistically significant (except for a_{mng} in the most recent cross-validation sets). Over time, we observe a drift in the coefficient estimates for *GDPpc* and a_{trad}, while $\widehat{RLP}$ is quite stable. This drift and the apparent lack of significance for $\widehat{RLP}$ in GLM4 are due to the interaction and do not give a sufficient impression of the combined effect of $\widehat{RLP}$ and a_{trad}, which is jointly significant in all cross-validation sets.

Fig. 3C provides a better visual impression of the joint interaction effect between $\widehat{RLP}$ and a_{trad}. The results support the expectation that high RLP reduces the likelihood of armed conflict when the traditional sector is large, where $\widehat{RLP}$ serves as a good approximation of RLP. For observations where agriculture and petty services constitute a smaller share of the economy (i.e., where a_{trad}

[7] The results are robust to predicting only one year into the future but predicting across a longer time period allows for greater variation in the outcome variable.

Table 1
Statistical models.

Model	Formula
GLM1	$ac \sim a_{mng} + \log(pop) + \Delta GDPpc + \log(GDPpc)$
GLM2	$ac \sim a_{mng} + \log(pop) + \Delta GDPpc + a_{trad}$
GLM3	$ac \sim a_{mng} + \log(pop) + \Delta GDPpc + a_{trad} + \widehat{RLP}$
GLM4	$ac \sim a_{mng} + \log(pop) + \Delta GDPpc + a_{trad} * \widehat{RLP}$
GLM5	$ac \sim a_{mng} + \log(pop) + grwt_{mng} + grwt_{trad} + grwt_{modern} + a_{trad} * \widehat{RLP}$
GAM1	$ac \sim a_{mng} + \log(pop) + \Delta GDPpc + s(\log(GDPpc))$
GAM2	$ac \sim a_{mng} + \log(pop) + \Delta GDPpc + s(a_{trad})$
GAM3	$ac \sim a_{mng} + \log(pop) + \Delta GDPpc + s(a_{trad}) + s(\widehat{RLP})$
GAM4	$ac \sim a_{mng} + \log(pop) + \Delta GDPpc + te(a_{trad}, \widehat{RLP})$
GAM5	$ac \sim a_{mng} + \log(pop) + grwt_{mng} + grwt_{trad} + grwt_{modern} + te(a_{trad}, \widehat{RLP})$

Note: All predictors are lagged one year to reduce the risk of measuring reverse causality. [9] s() is a thin plate regression spline, te() is a full tensor product smooth, see R package **mgcv** for details. Multiplicative interactions (*) also include the base terms.

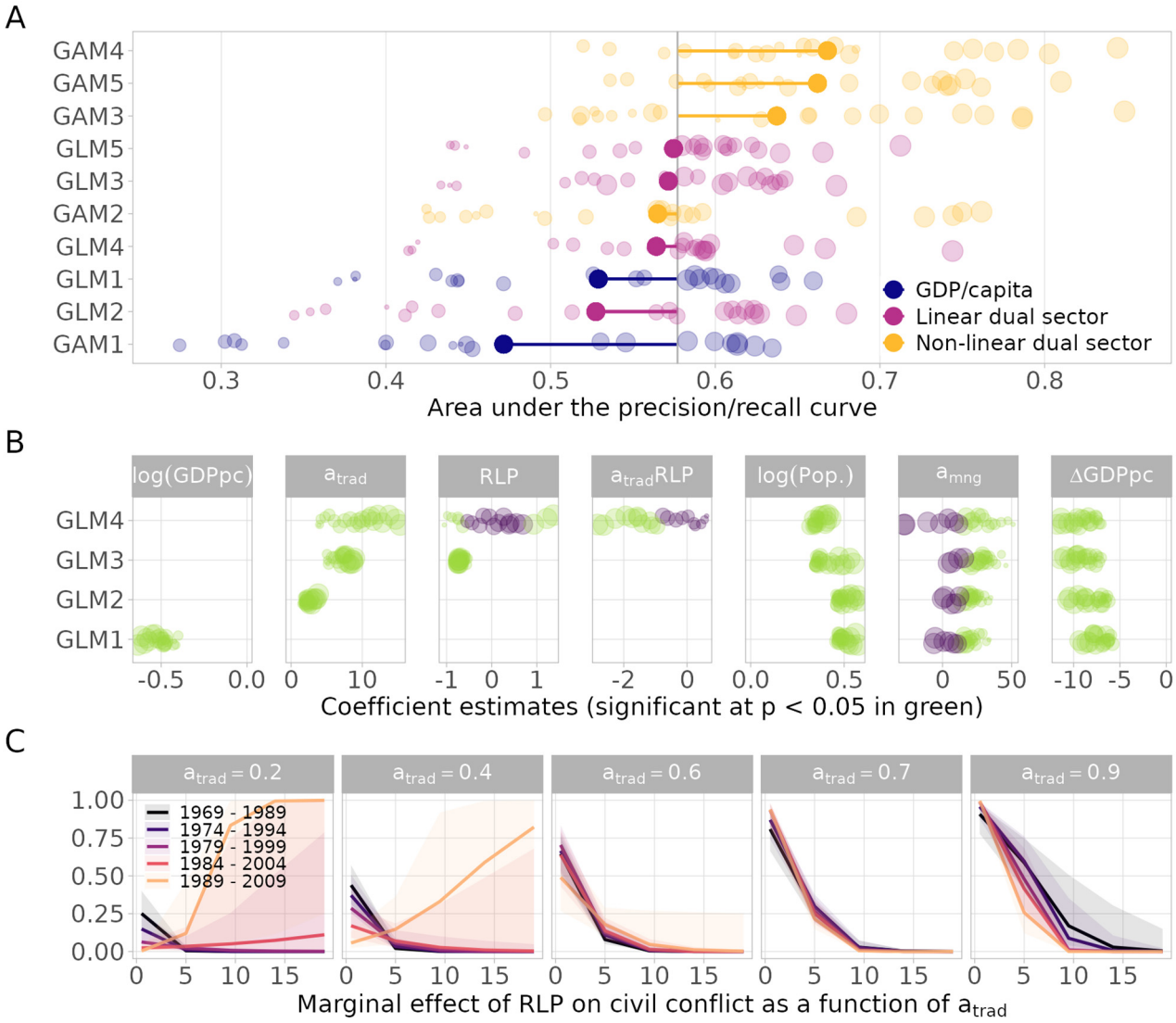

Fig. 3. Leave-future-out cross-validation. (A) LFO-CV performance across models with individual dots denoting AUC-PR score for specific training and test sets, where larger dots imply a more recent time period. Mean performance score for each model highlighted in bold, which is contrasted to the overall mean model performance across all specifications (vertical grey line). (B) Coefficient estimates and statistical significance for economic variables in the linear models. (C) Estimated marginal effect of RLP on conflict risk for different levels of traditional sector size, based on GLM4.

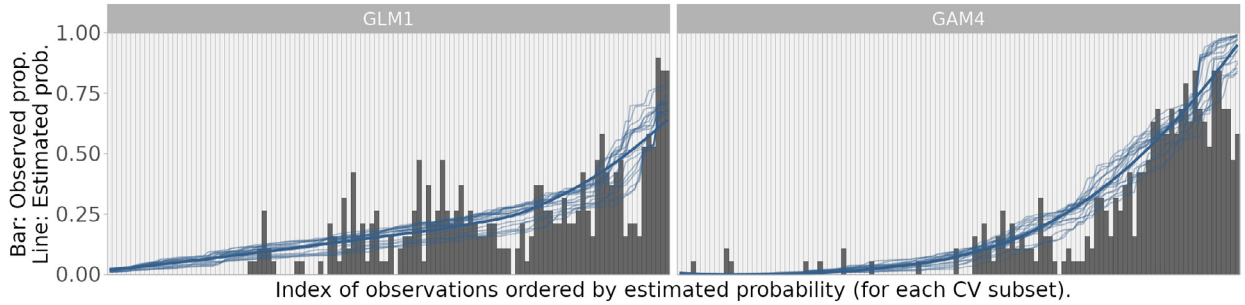

Fig. 4. Separation plots for GLM1 and GAM4. The plots display the estimated probabilities of civil conflict in ascending order from left to right with bars representing the proportion of true events at each index. A perfect model would result in clustering of all true events at the far-right end of the plot.

is small), the marginal effect of $\widehat{RLP}$ is smaller and much less stable across cross-validation sets. A likely reason for this is that in these countries, which have climbed much higher on the development ladder, $\widehat{RLP}$ no longer serves as a reasonable approximation of RLP. The additional sensitivity tests documented in Supplementary Materials substantiate the results presented in Fig. 3.

Fig. 4 shows a comparison between the best-performing *GDPpc* (GLM1) and dual sector model (GAM4), respectively. The plot is a variant of a separation plot, aggregated across all cross-validation sets. Two related patterns stand out: the dual sector model separates between conflict and peace years better than the GDP per capita model, and it also consistently assigns higher probability scores to observations with actual conflict and lower probability to observations that remained peaceful. In other words, GAM4 offers better separation than the benchmarking GLM1 both in terms of ranks and in terms of estimated probabilities.

Taking a closer look at individual predictions, GLM1 predicts particularly high likelihood of conflict in South Africa and China in the early 1990s, as well as in Nigeria, Zambia, Malawi, and Tanzania. Of these countries, only Nigeria experienced civil conflict within the next few years (1996). GAM4 also estimates high risk of civil conflict in China during the 1990s, but consistently predicts a substantially lower likelihood of conflict in Nigeria, Zambia, Malawi, and Tanzania (with a marked increase in estimated conflict risk in Nigeria in 2003, one year before the onset of civil conflicts in Northern Nigeria and the Niger Delta). While the dual sector-informed model represents an improvement on the common GDP per capita model almost across the board, it is especially suited to capture the particularities in the relatively peaceful experience in southeastern Africa.

Taken together, the analysis demonstrates that the benchmark economic model of civil conflict can be significantly improved by replacing GDP per capita with simple indicators of sector size and relative labor productivity. All else equal, the relative size of the traditional sector increases conflict risk whereas high relative labor productivity in the modern sector lowers the risk, but primarily for countries marked by a large traditional sector.

4.1. Extended analysis and sensitivity tests

The conflict-reducing effect of RLP is consistent with the classic dual economy model's emphasis on growth in real wages and hence increasing opportunity cost of rebellion. However, as briefly outlined above, high RLP may also be proxying for two other processes that reduce civil conflict risk: high state capacity and limited mobilization potential for rural challenger. While a complete evaluation of mechanisms and alternative explanations is beyond the scope of this article, we document a series of basic tests in Supplementary Materials Sections 3 and 4 that go some way toward assessing the relative credibility of these alternative interpretations.

In brief, we first explore whether high RLP inspires labor movement from the traditional to modern sector, as implied in the Lewis model. We find that high RLP is associated with growth in modern sector employment only among relatively democratic states, while being negatively associated with it in autocratic states. Since most countries with high RLP and a large traditional sector are autocratic, the opportunity cost mechanism is unlikely to be the main driving force underlying the conflict-reducing RLP effect.[8]

Having ruled out the explanation most consistent with our simple theoretical model, we also consider whether RLP instead could be proxying for high state capacity, which might both facilitate a burgeoning modern sector and deter rebellion. However, RLP is negatively correlated with common measurements of state capacity (e.g. bureaucratic quality, military expenditure), and RLP also does not seem to capture effects related to ease of doing business or education levels; low-income countries with high RLP are similar to other low-income countries on these indicators.

Our findings appear most compatible with resource mobilization theory (e.g., McCarthy & Zald, 1977; Tilly, 1978). High wealth generation, concentrated on a small (typically urban) elite, perhaps in combination with co-optation efforts by the state, lower the incentives for changing the status quo, and instead facilitate a protectionist privileged class that provides stability by denying access to networks and resources for aspiring rural challengers. Tellingly, RLP is positively correlated with the prevalence of corruption. Yet, the estimated negative effect of RLP on conflict risk does not diminish when corruption is introduced as a control, and corruption by itself generally increases conflict risk – opposite of RLP. Under this interpretation, therefore, RLP signifies what makes corruption a stabilizing force in a society. This tentative conclusion is based on limited data and is mainly arrived at through a process of elimination, rather than through positive empirical confirmation. We defer further probing into these mechanisms to future work.

In terms of sensitivity tests, we find that our main results generally are robust to key changes in the model specification, such as estimating civil conflict onset instead of incidence, adding conflict history to control for potential reverse causality, and changing the operationalization of the traditional sector (see Supplementary Materials, Sections S3–S5). In Supplementary Materials, Section S6, we replace the GGDC 10-Sector data with economic sector data from the World Development Indicators (WDI) (World Bank,

[8] The apparent conditional role of liberal democratic institutions in facilitating structural transformation (e.g., Acemoglu & Robinson, 2001; North et al., 2009) is an intriguing insight that deserves further scrutiny.

[9] Our variables of interest are partly endogenous to conflict exposure, which is associated with a relatively larger dependence on primary commodities and the traditional sector (Hegre, Nygård, & Ræder, 2017). We return to the issue of reverse causality in the discussion below and in Supplementary Material.

2020), permitting a global analysis for the post-1990 period by substituting measurement quality for sample coverage. In terms of overall performance, the ranking of the models is quite similar to those reported above, but the difference between single- and dual-sector specifications is smaller. We interpret the lower gain of the dual sector model to be due to the WDI data excluding important information on informal economic activities, which results in a poorer ability to separate between countries at similar income levels with markedly different conflict propensities. As a final test, we relax the dual sector modeling assumption and estimate all ten sectors included in the GGDC dataset as separate economic entities (Supplementary Materials, Section S7). Unsurprisingly, the much more flexible machine-learning algorithm provides predictions that better fit future observations than the GAM specification, although the results also reveal that employment shares tend to be better predictors than shares of value added – possibly pointing to the importance of structural conditions, and that mining, manufacturing, and agriculture are among the most important sectors to predict conflict risk.

5. Conclusion

GDP per capita has been identified as one of the most robust predictors of civil conflict (Colaresi & Mahmood, 2017; Hegre & Sambanis, 2006; Muchlinski et al., 2016). Yet, aggregate GDP statistics mask considerable heterogeneity in economic structures as well as conflict risk among developing countries. In this article, we have investigated the merit of disaggregating GDP per capita along the lines of Lewis' (1954) dual sector model to better capture the notable variation in conflict propensity among low-income countries and thereby improve our ability to predict future instances of civil conflict.

In line with expectations, accounting for relative sector size and relative labor productivity (RLP) significantly improves on our ability to predict civil conflict out of sample. This finding is consistent across time and robust to shifting model specifications. Many variables commonly included in analyses of civil war have been questioned on the basis of their poor performance in predicting conflict out of sample (Ward et al., 2010). The sector-sensitive models pass this hard test and outperform the benchmark economic model of civil conflict by some margin.

Subsequent tests reveal limited empirical evidence in support of the assumed wage determination mechanism, however, implying that opportunity cost is unlikely to be the dominant pathway driving the RLP effect. Instead, the empirical pattern appears most consistent with a resource mobilization interpretation, where the concentration of wealth on a small, status quo-oriented elite limits the ability of the marginalized to rise up against the regime. However, the restricted geographical sample of the analysis (40 countries) implies that the results reported here may not be fully representative of the world.

Our study points to important avenues for future research. An obvious priority is investigating further political determinants of the relationship between RLP, labor mobility, and growth in the modern sector. Likewise, the pathways through which high relative labor productivity lowers conflict risk, and the conditions under which this effect is most prominent, remain poorly understood. Expansion of the geographical scope of multi-sector economic data and validation of statistical findings through in-depth case studies studies are other promising avenues for future research.

This study has shown that a simple extension of the common GDP-based economic model of civil war, aided by sector-specific data on labor size and productivity, can provide novel insights into economic determinants of civil war. Notable restrictions in data coverage and limited ability to verify the main causal process underlying the RLP effect should not serve to discourage the significance of these insights but instead inspire more research into forms of economic development that are especially conducive to peace.

CRediT authorship contribution statement

Jonas Vestby: Conceptualization, Methodology, Data curation, Formal analysis, Validation, Writing - original draft, Writing - review & editing, Visualization. **Halvard Buhaug:** Conceptualization, Investigation, Funding acquisition, Writing - original draft, Writing - review & editing, Formal analysis. **Nina Uexkull:** Conceptualization, Investigation, Writing - original draft, Writing - review & editing, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2020.105273.

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