How Does Democratization Affect the Production of Knowledge?*

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Abstract

This paper investigates the relationship between democratization and knowledge formation. Using bibliographic and patents data, we show that there is a positive and strong impact of democratization on the formation of knowledge in social sciences and business but not in other fields and patenting activity. We confirm these findings using an instrumental variable approach to correct for the endogeneity problems, originating from the unobservables that affect both innovation and democratization and from measurement errors in quantifying democracy indices. Our instrumental variable results are in line with our baseline results. In fact, they indicate that there is a downward bias in the baseline result, which is likely to stem from measurement errors in quantifying democracy indices and unobservables. Finally, our results are robust to a number estimation methods, outliers, alternative construction of our IV, and different measures of human capital.

Keywords: Democracy, Knowledge Formation, Citation

JEL Classification: P16, O31, O43

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1 Introduction

The effects of democratic institutions on economic growth have been the subject of a wide range of economic studies. However, until recently, almost all studies found either a null or a negative effect. Gerring et al. (2005), in an extensive review of the literature on the effects of democracy, argue that the literature until the mid-2000s has found a negative or null impact of democracy on economic growth cross-nationally. This view has gained more attention in both academia and the public as the economic growth under an autocratic regime in China and some other nondemocratic states continues to be stable over time and as the consequences of the Arab Spring are dismal.

However, a handful of recent works have found a positive effect of democracy on economic growth. Papaioannou and Siourounis (2008), in an influential paper, show that democratization is associated with a 1% increase in GDP per capita growth. They propose a novel way of measuring democratization that has become very popular in subsequent works. A more recent paper by Acemoglu et al. (2019) also shows a positive relationship between democracy and income level.

The economic outcomes of democratic institutions in the literature have not been limited to economic growth. A vast literature have shown a positive relationship between democracy and other economic indicators, including but not limited to total factor productivity, corruption, government expenditure (for instance, Acemoglu et al., 2019; Baum and Lake, 2003; Alesina et al., 2016; Kotera and Okada, 2017; Bhattacharyya and Hodler, 2015). However, the effects of democracy on one of the most important determinants of economic growth, innovation, has been neglected. According to the endogenous growth theory, the formation of knowledge and new technologies has essential consequences on economic growth. (Solow, 1957; Romer, 1990; Jones, 2009).

We contribute to the literature by investigating the effects of democratization on knowledge formation in different fields all over the world in the period of 1980 to 2017. We put together a novel data set of citations received by academic papers and granted patents in various fields to study how democratization affects innovation. Our findings from a panel of countries between 1980 and 2017 show that democratization is associated with an increase in the level of formation of new ideas in social sciences and business fields while its effects in other fields are not conclusive.

Establishing a causal relationship between economic growth and innovation is cumbersome for several reasons. First, measurement error in reporting democracy indices is considerable. Glaeser et al. (2004) argue that democracy indices do not show perpetual characteristics of the environment. As Acemoglu et al. (2019) point out, this can lead to spurious changes in democracy indices while governments structures remain unchanged.

Second, correctly identifying the role of unobserved characteristics of democracies that also affect knowledge formation remains a challenging problem. For example, there are significant differences between democracies and autocracies in terms of cultural, historical, and institutional features. As a result, cross country estimations are less likely to show the correct causal relationship, if any, between democracy and innovation as they are susceptible to a number of biases.

Third, year and country fixed effects control for time-invariant characteristics of democracies and no-democracies. However, there is an endogeneity problem originating from time varying unobservables that might simultaneously affect democracy and knowledge formation. This leads to the omitted variable bias.

Forth, the majority of works that study the determinants of the knowledge formation function make use of patenting data as the outcome variable. On the one hand, patents do not include knowledge production in social sciences, business, and humanities. On the other hand, governments in authoritarian regimes are more likely to suppress publications and academicians in social sciences and business as the scientific findings in these disciplines might directly question the competency of authorities.

In our paper, we address all of these challenges. We build on the works by Acemoglu et al. (2019) and Bosetti et al. (2015) and construct a new data set to examine the effects of democracy on innovation. We employ a dichotomous measure of democracy, first proposed by Acemoglu et al. (2019), to tackle the first concern. In the data section, we carefully review the construction of this measure and its differences with other democracy indices. We address the second concern by employing a differences-in-differences approach with country and year fixed effects.

To address the endogeneity problem, we make use of the instrumental variable(IV) approach motivated by Persson and Tabellini (2008), Aidt and Jensen (2013), and Acemoglu et al. (2019). We discuss the validity of our instrument later in this paper. The instrumental approach relies on the fact that a transition to democracy for a given country often spreads to the other countries in a region. More specifically, we assume that shifts from autocracy to democracy in a given country can diffuse to the neighboring countries but do not have a direct impact on the level of knowledge formation in neighboring countries. We find similar results to the differences-in-differences estimations using the IV estimation approach though the magnitude of the coefficients is higher.

Finally, we employ the yearly citation data reported by Scopus to measure the level of knowledge production in all fields, including social sciences, business, and humanities. We complement our data with the data on patenting activity to further investigate the effects of democracy.

The rest of the paper is organized as follows. Section 2 reviews the related literature. In section 3, we propose a simple model of knowledge formation. Section 4 describes the construction of our data. In section 5, we present the empirical approach of the paper. Section 6 shows the results of the differences-in-differences estimations. Section 7 develops and presents the estimation results from the IV estimation approach. In section 8, we present the results of the robustness checks. Section 9 further explores the validity of our instrument. Section 10 concludes.

2 Literature Review

This paper relates to the literature in several ways. First, it contributes to the growing literature on the political economy of growth. Within this area, it mostly links to the works in which governments sometimes block innovation and economic development due to vested economic interests. Krusell and Rios-Rull (1996) formalize a model in which technology adaptation plays a self-destructive role. According to their model, incumbent innovators have a decent amount of political power to block new technologies. Acemoglu and Robinson (2006) show that political elites tend to prevent economic development due to their fear of replacement that can be potentially brought by technological progress. Besides these two influential works, a handful of papers put emphasis on the role of conflicts between agents on economic development (e.g., Restuccia, 2004; Bellettini and Ottaviano, 2005; and Bridgman et al., 2007).

Second, our work adds to the literature on the persistence of power, policies, and the role of institutions in economic development. Acemoglu (2008), Acemoglu and Robinson (2006), Acemoglu et al. (2008, 2009, 2015, 2019), Papaioannou and Siourounis (2008), and Persson and Tabellini (2006, 2008) emphasize the positive role of institutions in general, and democracy, in particular, on economic growth. Other papers have linked institutions and economic development, government expenditure, corruption, patent intensity, etc. Bhattacharyya and Hodler (2015), employing a difference-in-differences approach, find that democratization has a positive impact on the reduction of political corruption. Using the same approach, (Kotera and Okada, 2017) do not find a significant effect of democratization on total government expenditures, but a positive effect on governments expenditures on health. In this regard, a number of papers have focused on the impacts of population diversity on economic development. Alesina et al. (2016) consider TFP per capita and patent intensity as the indicators of economic development to examine the relationship between birthplace diversity and economic prosperity.

A large body of literature have investigated the effects of micro-level institutions (e.g., universities, research institutions, etc.) on knowledge formation. Institutions can facilitate access to knowledge by improving the tools via which reliable knowledge is obtained (Mokyr et al., 2002). Furman and Stern (2011) refer to these institutions as research-enhancing institutions. Most of the work investigating the role of research-enhancing institutions make use of citations to scientific papers or the number of granted patents to study the effects of existing knowledge on current developments. Among others, Jaffe et al. (1993) and Henderson et al. (1998) examine whether citations to patents received by universities with a broader geographical scope are more considerable than "control" patents extracted from comparable geographic locations. They all find a direct relationship between research-enhancing institutions and the formation of knowledge. Furman and Stern (2011) examine the impact of a particular type of institution, a biological resource center, that is responsible for verifying and distributing knowledge. Using a difference-in-differences methodology, they discover that institutions can intensify the effect of individual knowledge formation.

An essential aspect of the role of institutions in economic development is the property and individual rights. Property rights are one of the components of both the Freedom House and Polity IV scores. Patent rights can be considered as a central part of property rights, and they are the subject of a wide range of economic studies on knowledge formation. Most of the research in this area, however, has been inconclusive. Theoretically speaking, the "prospecting theory" suggested by Kitch (1977) argues that patent rights amplify cumulative innovation. In contrast, a handful of papers have argued that patent rights can impede the formation of new ideas when bargaining between the patent parties is not efficient (see, for example, Bessen and Maskin, 2009 and (Galasso and Schankerman, 2010)). As to the empirical work on the topic, an influential paper by Murray and Stern (2007) is the first work to provide causal evidence of the negative impact of intellectual property rights on subsequent research in the biomedical field. In addition, Galasso and Schankerman (2015) show that patent rights block innovation in most fields and mainly depend on the bargaining environment.

Third, this paper also contributes to the literature on the determinants of knowledge production function and the endogenous growth theory. According to the endogenous growth theory, the formation of knowledge and new technologies have important consequences for productivity and growth (Romer, 1990; Grossman and Helpman, 1991). Hence, A wide range of studies have investigated the determinants of innovation. From the theoretical point of view, the association between innovation and its determinants has not been straightforwardly defined despite a large number of empirical studies on the topic. (Stern et al., 2000), propose a fundamental function for national innovative capacity. Following (Stern et al., 2000), most of the empirical pieces of research done on this area have assumed that knowledge production is a function of R&D and human capital (HK) levels in a given country as well as its regional neighborhood countries (e.g., Bode, 2004; Ponds et al., 2009; Fagerberg et al., 2014, and Charlot et al., 2015). Crescenzi and Rodríguez-Pose (2013) add a socio-economic index to the function of knowledge formation that includes the sectoral composition of the economy. They conclude that social conditions are necessary to boost the productivity of innovation efforts. Migration is another factor that may impact knowledge production. Bosetti et al. (2015) show that the number of granted patents and citations received by academic papers increases as the rate of migration to the European countries grows. Baum and Lake (2003) find that democracy has a positive effect on secondary education in non-poor countries.

3 Data

We construct two unbalanced annual panel data sets to measure knowledge production, citation information, and patent. Because the citation data is available from 1996, our first data set comprises 129 countries from 1996 to 2017. As for the patenting activity, our data set contains 129 countries from 1980 to 2018.

We mainly make use of the dichotomous measure of democracy developed by Acemoglu et al. (2019) to quantify democracy. Although they construct their measure based on the index introduced by Papaioannou and Siourounis (2008), the two indices are not the same. The main difference is that Papaioannou and Siourounis (2008) only consider permanent transitions from nondemocracy to democracy, while Acemoglu et al. (2019) take into account all types of democratization, including reversal transitions. The major drawback of Papaioannou and Siourounis (2008)'s index is that when reversals are not considered, their index worsens the endogeneity problem by encoding information on the future status of democratic institutions. Hence, we believe that the democracy index developed by Acemoglu et al. (2019) measures democracy more efficiently.

As we basically utilize the dichotomous index by Acemoglu et al. (2019), we briefly review how they form their index. This index relies on Freedom House and Polity IV scores. Freedom House publishes the institutional score in three different categories. The first one is the general level of democracy in a given country and codes countries as "Free", "Partially Free", "Not Free". The other two measures are Civil Liberties and Political Rights scores. The two later ones range from one to seven. A score of one represents the highest level of freedom and seven the lowest level of freedom. On the other hand, the Polity IV score shows the political regime democracy level on a 21-point scale ranging from -10 (full autocracy) to +10 (full democracy). Considering Freedom House's general score and Polity IV index, a country is coded as free if its general Freedom House score is either "Free" or "Partially Free", and it also has a positive Polity IV value. Finally, if a country is coded as "Free" or "Partially Free", its score is one. Otherwise, it receives a score of zero. This democracy index measures a wide range of modern democratic institutions' characteristics, including free elections, constraints on executive power, and more importantly for our work, civil rights as the latter is one of the main components of the Freedom House's score.

The data provides democracy information for 184 countries. Out of 4,049 country/year observations, 2,757 are indexed as democratic while 1,292 are autocratic. Once we consider countries for which other variables of interest are available, we are limited to 129 countries. This results in 38 and 29 events of democratization and reversals, respectively. [1] In addition, Figure 1 shows the evolution of the dichotomous measure of democracy, along with two other indices for the whole world and seven regional categorizations that we employ for our IV estimation (Sub-Saharan Africa, East Asia and the Pacific, Europe Central Asia, Latin America and the Caribbean, Middle East and North Africa, and North America).[2]

Our main outcome variable is innovation. Finding a valid proxy for knowledge formation is cumbersome and is still a subject of debate. Patents data are the most commonly employed proxy for innovation. Patents are legal titles for a specific product or an idea to be protected by patenting authorities when granted to the assignee. The major drawback of patents data in the context of our paper, however, is that not all new ideas are patented, and that the patenting activity is endogenous to the level of income and economic development of a given country, especially given the presence of financial and institutional entry barriers. In addition, the patent granting system is constructed in such a way that a patent office grants monopoly rights for a short period of time to innovations that are applicable in industry. However, knowledge formation is a concept much broader than the number of patents granted. More importantly, patents are mostly granted to the STEM fields. Consequently, by only considering patents data, we would not be able to capture the effects of democracy in social sciences, business, and humanities. Hence, we make use of another measure of innovation, bibliographic data, that is more strictly linked to pure research and entry barriers are lower than those in patenting activity. These measurements allow us to break down the effects of democracy by academic fields.

Utilizing patent and bibliographic data as proxies for knowledge production raises a significant concern regarding the quality of new ideas. To address this concern, we carefully choose two measures that are highly associated with the impact and quality of innovation. As for the patents data, we take into account the layout of the patent system to choose our variable of interest. There are different routes for inventors in order to protect their innovation. Specifically, applying for a patent can be done in a national office or via the

Patent Cooperation Treaty (PCT). The former will result in receiving patent rights in a single country or market while the latter gives the applicant patent rights in more than one country, and in some cases, globally. It needs to be mentioned that applying via PCT is both time and money consuming. We only employ PCT data in order to consider the high-quality patents and remove the lower quality ones from our sample. With regard to bibliographic data, we consider an assumption employed by Bosetti et al. (2015), assuming that influential knowledge has a strong influence when subsequent knowledge uses it to proceed. According to this assumption, we conclude that highly-cited publications are of higher quality as well. In addition, countries with a high number of researchers publish more. As a result, we use citations per document in order to adjust our measure for the number of publications.[3] Citation data have been previously used in the literature as an indicator of the impacts of universities or national output (see, for example, Stuen et al., 2012 and King, 2004). Patenting data are obtainable from the World Intellectual Property Organization (WIPO, 2020). The SCImago Journal & Country Rank provides detailed data on the number of papers and the number of citations by country, year, and academic field.

According to our model, we need data on the available stock of knowledge to researchers and the total number of researchers. A good proxy for the available stock of knowledge is the past innovation efforts.[4] As for the total number of researchers, these data are not available for most developing countries.[5] We address this concern by adding a human capital index and a variable for the total number of people who are engaged in the labor market. Also, our measure of innovation in the citation sample partly addresses this issue.

As for other control variables in our investigation, we use GDP per capita (constant 2010 $US), openness (measured by real exports and imports as a percentage of GDP), population, human capital, the number of persons engaged in the labor market from the Penn World Tables (PWT 9.1), and tertiary education from the World Development Indicators (2019). Descriptive statistics for all the variables we use in this paper are presented in Table 1.[6] This table reveals important patterns regarding the difference between democratic and non-democratic countries. Democratic states have a higher level of income and publish more high-impact documents.

4 A Simple Model of Knowledge Formation

The role of political and social freedoms on economic growth has widely been investigated in the literature. However, there are only a handful of papers studying the effects of freedom on productivity. Productivity has mostly been considered as a channel through which freedoms affect economic growth. In addition, in almost all studies, productivity has been measured by total factor productivity that evaluates an economy as a whole.

According to endogenous growth theory, the formation of knowledge and new technologies have essential effects on economic growth and productivity. We slightly alter the model presented by Bosetti et al. (2015) to propose a simple model explaining the relationship between freedoms and innovation production. In this model, innovation, I, is a function of number of researchers, S, and the average researchers' productivity, δ.

$$I = S\delta \tag{1}$$

We make another assumption that the average productivity of a given skilled worker is a function of past innovations, A, number of researchers, S, and freedoms, F. Hence,

$$\delta = (A^{\alpha})(F^{\beta})(S^{\gamma-1}) \tag{2}$$

And therefore:

$$I = (A^{\alpha})(F^{\beta})(S^{\gamma}) \tag{3}$$

Equation (3) is the basis of this paper to investigate the relationship between freedoms and productivity.

5 Empirical Methods

In this section, we use the annual data for 128 countries over the period 1996–2017 to investigate the effect of democratization on citations per document. Following Papaioannou and Siourounis (2008) and Acemoglu et al. (2019), the main linear regression model takes the following form in Equation (5).

$$ln(y_{it}) = \beta_1 D_{it} + X_{it}^{'}\Gamma + \alpha_i + \gamma_t + \epsilon_{it} \tag{4}$$

The dependent variable, $ln(y_{it})$ is the total number of citations per document or total patents granted in country i in year t. Our main variable of interest is D_{it} which is the dichotomous measure of democracy in country i in time t. $X_{it}^{'}$ is a vector of control variables in country i in year j including two indices for the level of human capital and available stock of knowledge to researchers. We also control for other variables that can affect our outcome variable, including GDP per capita, openness, and the total number of people engaged in the labor market. Additionally, year fixed-effects (γ_t) and (α_i) country-fixed effects control for global trends and time-invariant country characteristics, respectively.[7]

Equation (5) forms a difference-in-difference model where democratized countries are the treated group, and non-democratized countries serve as the control group. As we include country and year fixed-effects, D captures the effect of democracy in democratized countries compared to the general level of knowledge production in non-reforming countries. Difference-in-difference models have gained more attention in macroeconomic works recently since they address a wide range of limitations of cross-country estimations. With regard to our paper, they can account for time-invariant country characteristics, such as social norms and geography, that may affect both innovation and institutional development. Finally, the model also accounts for global trends that are common in all countries.

The differences-in-differences regression can be biased if the treatments are not random, or if the treated and control countries are systematically different from one another. Such biases may still be present in a macro context and cannot be completely ruled out. As a result, we need to be careful in interpreting our results. However, we make progress by addressing these concerns to be confident we are capturing the causal effects. As discussed earlier, country and time fixed-effects already eliminate biases arising from time-invariant country characteristics and common global trends that may influence both innovation and treatment.

The treated group may be systematically different from untreated countries in the absence of parallel trends before the treatment. Figure 2 shows the average number of citations per document in treated and control countries. It provides explicit support for the parallel trend assumption. It is not possible to present a figure like those shown in micro contexts. This is mainly due to the fact that democratization happens in countries at different years, and there is not an exact treatment time. As a result, we go through a different path to test this assumption. The top panel of Figure 2 presents the average number of citations per document in control countries from 1996 to 2017. In the bottom panel, we plot the same variable in treated countries from seven years before to seven years after the treatment year. In the bottom panel, we plot the same variable in treated countries from seven years before to seven years after the treatment year. In our analysis, we need to take into account that previous publications can always be cited by subsequent publications. Hence, the total number of citations received by a given paper increases over time. That is why the graph is downward sloping for the control group. On the other hand, the graph for the treated group displays a downward sloping line before the treatment for all fields. However, after the treatment, we only observe a clear upward trend for two fields: social sciences and business.

Figure 3 presents the same analysis for the patents data. However, it displays a different pattern. Patenting activity shows a sharp fall following the democratization time and then gradually increases over time. As mentioned earlier, applying for PCT patents is highly costly, and researchers need to be supported by governments. One reason might be what Papaioannou and Siourounis (2008) refer to as "costs of transitions". They argue that countries experience a fall in the income level right after an event of democratization. Another reason might be the fact that in many cases, a transition from autocracy to democracy is following a crisis (Haggard and Kaufman, 1997) which suggests that we may need to be cautious in interpreting the patents regressions results.

6 IV Approach

As discussed above, our estimation method controls for the effects of time-invariant unobserved characteristics. In this section, We employ an instrumental-variables (IV) strategy developed by Acemoglu et al. (2019) to address the endogeneity concerns in this section. There are two issues that can be addressed by a valid instrument. First, there might be some time-varying omitted variables that can affect the occurrence of a democratization event and subsequent knowledge formation at the same time. Second, the democracy index is subject to measurement error or more specifically, endogenous selection into democracy.

Transitions from an autocracy to a democracy usually happen in regional waves. A wave of democratization in the 1970s turned a large number of countries in Latin America and the Caribbean into democracies. This is also followed by another wave in the 1980s and 1990s. At the same time, after the disintegration of the Soviet Union in the 1990s, a large number of countries in Central Asia, Africa, and Eastern Europe underwent a democratization process. The most recent wave of democratization is the experience of the Arab Spring.

There is a vast literature on the factors affecting such waves. Acemoglu et al. (2019) argue that economic trends cannot account for democratization waves. Bonhomme and Manresa (2015) provide evidence that democratization is highly correlated within regions. As discussed theoretically and empirically in the literature, it suggests that democratization scatters across countries in the same region, which share similar backgrounds, governing structures, and close social norms.

Though Acemoglu et al. (2019) construct their IV based on the work of Persson and Tabellini (2008), these two are notably different. Persson and Tabellini (2008) use neighbors' democracy according to an inverse distance-weighted measure. But Acemoglu et al. (2019) assume that democratization occurs regionally and exploit the regional classification of countries based on the World Bank categorization. Equation (**??**) represents the formal specification of the IV.

$$Z_{it} = \frac{1}{N_{rinit} - 1} \sum_{i' \in r, D_{i' init} = D_{iinit}, i' \neq i} D_{i't} \tag{5}$$

Here, r represents one of the seven regions classified by the World Bank.[8] D_{iinit} is a the dichotomous measure of democracy taking a value of one ($D_{iinit} = 1$) if the country was initially democratic ($D_{iinit} = 1$) or zero ($D_{iinit} = 0$) if the country was autocratic at the first time it becomes available in the sample. Finally, N_{rinit} measures the number of countries in that region. Because democratization in a given country does not affect political regimes in the neighboring countries immediately, we make use of the first lag of Z as the instrument for democratization. The two-stage least squares ($2SLS$) model can be estimated by

$$ln(y_{it}) = \beta_1 D_{it} + X_{it}^{'}\Gamma + \alpha_i + \gamma_t + \epsilon_{it} \tag{6}$$

$$D_{it} = \pi_j Z_{it-1} + X_{it}^{'}\Psi + \theta_i + \delta_i + \nu_{it} \tag{7}$$

The most important assumption here is that the exclusion restriction condition holds.[9] The economic justification is that, conditional on the other covariates, year and country fixed effects, democratization has no direct impact on innovation.

7 Emperical Results

Table 2 reports the results of the estimation of equation (5) controlling for a numbers of variables for a sample of 127 countries between 1996 and 2017. We cluster standard errors in all regressions at the country level to control for possible serial correlation within countries. The dependent variable is the total number of citations per document. Column 1 regresses the number of citations in all fields on the democracy index developed by Acemoglu et al. (2019). While we control for income levels, we do not include the other control variables in this regression. The main reason for excluding other control variables is the fact that we might be over-controlling for the other factors that can affect knowledge formation. In particular, one might argue against including human capital index as it is a very slow-moving variable. Column 2, which is our preferred specification, shows the effect of democracy on citations including all control variables. We find no significant effect of democracy on the total level of knowledge production using the citations data. Also, the estimated coefficient on democracy in column 2 is twice as much as the one in the first column, although they are both insignificant. For comparison, we report the effects of the other measures of democracy on knowledge formation in columns 3-7. Other than the polity IV score, which is marginally significant, the effect of democracy on citations per document is not significant.[10] Nevertheless, the estimated coefficient on democracy in our preferred specification is greater than the other democracy indices.

With regard to the control variables, the effect of the existing stock of knowledge, as expected, on the current level of knowledge production is positive and significant in all columns. To control for the effects of the number of skilled researchers, we include two variables for human capital and the total number of people engaged in the labor market. In addition, since our main dependent variable is total number of citations per document, it also captures part of the effects of the number of researchers. Our results indicate that there is no statistically significant effect of a larger pool of researchers on knowledge formation. As mentioned earlier, one possible explanation is that the stock of knowledge and the structure of the dependent variable already partially account for the researchers' population. Another reason could be the effect of decreasing return to labor. As suggested by Bosetti et al. (2015), duplications, overlaps, and negative congestion externalities are the results of an increase in the number of skilled researchers.

We now turn to the heterogeneous effects of democratization on knowledge production. Table 3 displays the effect of democracy on citations by fields. Scopus annually reports the total number of citations and publications for a given country in 27 different fields. However, many journals are assigned to more than one field. For instance, the Journal of Econometrics is counted in three different fields, including Economics, Mathematics, and Humanities. As a result, this categorization prevents us from forming an aggregated measure of our preferred classification. Hence, we choose five different fields of study which are assumed to be representative of all fields.[11]

As discussed above, we first exclude control variables and then do the same exercise, including all of them. Columns 1 through 6 report the regression results without the control variables. Columns 1 and 7 show the result of our preferred specification in Table 2, and the rest of the table explores the heterogeneous effects of democracy. While the magnitude of the coefficients does not change much once we include all control variables, the estimated coefficient on democracy on Business becomes insignificant.[12] Other than social sciences and business, the effect of democratization on knowledge production is not significant in any fields. The coefficient on the democracy variable for Social Sciences is 0.155 (standard error=0.0782) and significant at 5% level, meaning that academic publications in social sciences in democracies receive around 16% more citations per document than the ones in non-democracies. The coefficient of democracy for business is close to the one for social sciences. The estimated coefficients of democracy in the other fields are positive and of a smaller magnitude compared to social sciences and business. Even though, to the best of our knowledge, there is no academic work on how governments in authoritarian regimes target professors and academicians, the evidence is abundant in policy discourse. In one case, Berat Albayrak, the Minister of Treasury of Turkey, after an economic turmoil, threatened economists by saying

"Economists and academics who state that the economy is getting worse are terrorists."[13]

Likewise, the Study International argues that "academic papers by university professors are rigorously monitored in China, and anything critical of how the country is run is immediately censored".[14]

With regard to human capital and available stock of knowledge to researchers, the results are mostly similar to those in column 1. Once again, we do not find any significant effect of human capital on knowledge formation, while the effect of the available stock of knowledge (not reported) to researchers is again positive and significant.

We now turn to the results of our IV estimation. Table 4 presents the effects of democratization on innovation using a $2SLS$ estimation method as specified in equations (6) and (7). The identification is based on the fact that transitions to democracy are influenced by democratization in neighboring countries. In addition, democratization in neighboring countries is unlikely to influence innovation directly. Consequently, the constructed instrument for democratization is valid as the correlation between the IV and democratization in a given country is positive. Moreover, the IV does not directly impact the outcome variable. We first confirm the validity of the instrument from the statistical point of view. The bottom panel of Table 4 presents the first-stage regression for democratization. As expected, the correlation between the constructed instrument and democratization is positive. The F-values in all columns for the tests of the excluded instruments in first-stage regressions surpass 10.[15] It satisfies the "rule of thumb" suggested by Staiger and Stock (1997).

We again report regressions with and without control variables and find similar results. In the seventh column of the top panel, we find that democratization, contrary to the OLS estimation, is positively correlated with the total number of citations per document. Moreover, the magnitude of the estimated coefficient on democracy is much higher compared to the one estimated in the OLS regression. The coefficient on the democracy variable is 0.345 (standard error=0.284) and significant at 10% level, meaning that academic publications in democracies receive around 35% more citations per document than the ones in non-democracies. The fact that our IV estimations produce greater effects of democracy on citations might be due to two factors. First, it might be due to some of the factors causing downward biases as mentioned before. Second, measurement error led to attenuation bias. In addition, the IV estimation method controls for the effects unobservables simultaneously affecting both the democratization in different countries as well as the evolution of scientific papers. Another reason for the difference between our OLS and 2SLS results is the Local Average Treatment Effect. Even though our OLS results show the average difference in citations per document, the 2SLS results is only for those whose democratization was affected by the instrument in use (for regional changes).

The rest of Table 4 focuses on the heterogeneous impacts of democratization. Column 8 presents the effects of democracy on the total number of citations per document in the field of engineering. Unlike the OLS results, the impact of democratization on this field is significant and positive. The estimated coefficient is 1.369 (standard error=0.639). We later discuss some possible explanations for this change. As for other fields, we find no significant impact of democracy on the field of medicine, while this impact is positive and significant in agriculture. Among all fields, the estimated coefficients of democracy on social sciences and business are highly significant and of a higher magnitude. The coefficient on the democracy variable for Social Sciences is 1.885 (standard error=0.759) and significant at 5% level, meaning that academic publications in social sciences in democracies receive around 190% more citations per document than the ones in non-democracies. The estimated coefficient on democracy for business is even higher. In Particular, academic publications in business in democracies are cited around 216 % more compared to the ones in autocracies. This confirms our findings in the OLS regression.

Thus far, we have discussed our findings on the effects of democratization on citations. We now turn to explore the effects of democracy on patenting activity. Table 5 summarizes Tables 2, 3, and 4 for the patent sample. Our patents sample consists of 129 countries between the years 1980 and 2017. Column 6 focuses on the effects of democratization on the total number of patents granted employing the democracy index proposed by Acemoglu et al. (2019). Column 6 reports the estimated coefficient on democratization patents using the OLS estimation. We find a very small, negative, and insignificant impact of democracy on patenting activity. Columns 1-5 explore the same effect employing the alternative measures of democratization. In Column 7, we estimate the effects of democratization using the IV approach. The estimated coefficient on democracy is again negative and insignificant but of a higher magnitude. This confirms our findings in Figure 3. As shown in Figure 3, democratization is followed by a sharp fall in patenting activity. One possible explanation could be what we mentioned earlier as the "costs of transitions". The other possible reason might lie on government expenditures. As applying for patents is highly costly and it associates with a high level of risk since the application could be rejected, researchers need to be supported by governments. However, as it has been discussed in the literature, democratization has no significant impact on government spending on education (for example, Mulligan et al., 2010; Kotera and Okada, 2017). On the other hand, many works have found a negative and significant impact of democracy on government expenditure on defense (Dunne et al., 2008; Albalate et al., 2012; and Ünal Töngür et al., 2015). Since many patent fields are military-related, the decrease in government expenditure might be the other possible reason. To sum up, our findings on the effects of democratization on patenting activity need to be interpreted with caution.

8 Robustness Checks

One concern regarding the citation data is the issue of self-citations. We check the sensitivity of our findings by subtracting self-citations from total citations and re-estimate the model. The results are presented in Table 6. Our results indicate that self-citations are not a major issue as our results are mainly the same as what we found in Table 4.

To control for the number of researchers, we employed the human capital measure from the PWT, along with the total number of people engaged in the labor market. We now replace the human capital index with an index for tertiary education. The results are shown in Table 6. While the estimated coefficient of democracy on the total number of citations per document in social sciences, agriculture, and business remains almost unchanged compared to our results from Table 4, the coefficient of democracy for engineering changed considerably. As shown in column 2, the effect of democracy on total number of citations per document in the field of engineering is not significant. Furthermore, unlike Table 4, the effect of our proxy for the number of researchers is significant. It suggests that human capital level is a major driver of publications in engineering, and we need to be careful about our earlier findings.

In Tables 8 and 9, the sensitivity of our findings to outliers is checked. Particularly, we exclude countries with a standardized residual above 1.96 or below -1.96 and re-estimate our main specification. As another check to explore the sensitivity of the results, we exclude couturiers with a Cook's distance above the common threshold.[16] The results, in both cases, are quite similar to our findings in the main section, suggesting that our results are not affected by outliers.

Finally, we check the robustness of our findings regarding the patenting activity.[17] The results are presented in Table 10. Column 1 shows our baseline specification. Column 2 replaces the human capital index with tertiary education. In Columns 3 and 4, we control for the effects of ateliers as specified above. In all columns, the effects of democratization on patenting activity is fairly small, negative, and insignificant.

9 Additional checks on the IV estimation

Although we believe that the construction of our instrument is intuitive as it has been discussed in the literature, there might be some concerns over the results of the IV estimation results. A major concern is the fact that the magnitude of the coefficients inflates dramatically. Another concern arises from the difference between the significance levels of the estimated coefficients in our baseline estimation and IV ones. In particular, the estimated coefficients on total number of citations per document, and in the fields of engineering and agriculture become significant in our IV estimations. In this section, we address these concerns. We first explore the intuition behind the construction of our instrument to make sure our instrument is a good one and then present the estimation results from alternative instruments.

We first check whether democracy is more likely to diffuse within region * initial regime cells as specified in the IV approach or if it diffuses more rapidly to neighbors. To do so, we employ the data on the latitude and longitude of countries to calculate the average of democracy in neighboring countries, and the weighted average of democracy in other countries given their inverse distances to a certain country. We also employ the data from CNTS to construct a variable of political unrest as a proxy for political discontent to explore the diffusion patterns of unrest.

Table 11 shows the results of regressing the dichotomous measure of democracy of a given country on its own lagged level of democracy, lagged regional democracy, lagged distance weighted democracy, and lagged average democracy in neighboring countries. A full set of country and year fixed effects are included in all regressions. The results of the estimations suggest that transitions to democracy are highly correlated with its own lags but not greatly with lagged regional democracy and lagged distance weighted democracy. Our results contradict the findings of Acemoglu et al. (2019)'s paper as they find lagged regional democracy is the main determinant of transitions to democracy following lagged democracy. There are two reasons that can explain this difference: first, our dataset is not as lengthy as theirs and second, we cover eight years that are not included in their dataset. More specifically, our dataset covers the years after the occurrence of the Arab Spring, while theirs ends right before this phenomenon.

To further investigate the determinants of the innovations to democracy, we study the diffusion patterns of unrest. Table 12 shows the results of the spatial diffusion patterns of democracy. Interestingly, we cannot make a conclusive conclusion regarding the main factor responsible for transitions to democracy. Depending on the specification of the model, either of lagged regional democracy, lagged distance weighted democracy, or lagged neighbors' democracy might explain transitions to democracy. Once again, our findings are not consistent with Acemoglu et al. (2019)'s paper.

We replace our instrument with a new one and repeat the same exercise as specified in equations (6) and (7). The new instrument is the lagged neighbors' democracy.[18] Table 13 shows the estimation results. While the effect of democracy on total number of citations per document is almost the same as Table 4, some important changes are observed.[19] First, the magnitude of the coefficients for all fields are less than half of the ones we found in Table

4. For example, the estimated coefficient of democracy on citations per document in social sciences is 0.887, meaning that transitions to democracy, on average, increase the number of citations per document in social science by around 90% while it was around 200% in Table 4. Second, the effect of democracy on citations per document in engineering is not significant anymore and its magnitude is much lower than what we observed in Table 4.

In short, while our main argument still strongly holds as the effect of democracy on social sciences and business is highly significant and sizable, our new results cast doubt on our finding in Table 4 on the effects of democracy on other fields. It should also be noted that once we changed the human capital index, knowledge formation in engineering was not impacted by democracy. Our findings in Table 13 are consistent with our findings in our baseline regressions.

10 Conclusion

While the effects of democracy on a wide range of economic indicators have been studied in the literature, its effects on innovation have been neglected. As suggested by the endogenous growth theory, new ideas are essential for economic growth. In this paper, we explored the effects of democratization on knowledge formation using the democracy index developed by Acemoglu et al. (2019). To quantify the formation of new ideas, we made use of two indices proposed by the literature: citations to academic papers and patenting activity.

To address the endogeneity problem originating from the measurement error in quantifying the democracy index and observable factors which simultaneously affect both democratization and knowledge formation, we employed an IV estimation strategy. Our IV method relies on the fact that democratization can spread to the neighboring countries while it cannot directly affect knowledge production in other countries.

We found a significantly positive impact of democracy on total citations per document. As for the heterogeneous impact of democratization, we detected a pronounced and robust positive effect of democracy on citations per document in social sciences and business. We also found positive effects for the other fields but we need to be cautious in how we interpret them. While the effects of democracy on the number of citations received by publications in the field of engineering is positive in our main specification, it is highly sensitive to the measure of human capital and becomes insignificant once we control for tertiary education. Regarding our patents data, we did not find any significant effect of democratization on patenting activity. While we provided possible explanations for our results, we believe further research needs to be done to reach conclusive conclusions.

Notes

[1]Tables 1 and 2 in the Appendix present a detailed review of democratizations and reversals.

[2]For years before 1996, we provide the same figure in Appendix.

[3]Our analysis for the citation data stops at 2017, while the SCImago (2020) dataset reports citations to all scientific papers published from 1996 to 2020. According to the literature, citations reach their peak after three years. Therefore, our analysis is reasonable. We will also report the estimation results excluding years 2016 and 2017 in the Appendix.

[4]We discuss how to measure past innovations in the Appendix.

[5]These data are only available for one thousand observations which are one-third of our sample

[6]We present an extensive form of this table, including patents data for 35 different fields in the Appendix.

[7]Murray et al. (2016) argue that an increase in the level of openness motivates researchers to enter another country.

[8]East Asia and the Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia, and Sub-Saharan Africa

[9] We later statistically show that the instrument is valid and strong.

[10]It also shows that the correlation between democracy indices is high.

[11]Business is an exception here. We chose it due to its important implications in the context of our paper. In the Appendix, we report the estimation results for all fields.

[12] It is exclusively the effect of the human capital index. Although not reported here, we ran a regression by only excluding the human capital index and the effect of democracy on business was significant at 10% level.

[13]YANICAG, November 7, 2019. Link

[14]Study International, August 5, 2019. Link

[15]The F-Stat here has been proposed by Kleibergen and Paap since the Cragg-Donald Wald F statistic is not valid for robust standard errors.

[16]Four divided by the number of observations.

[17]In the appendix, we will present another set of robustness checks including time-varying effects and estimation results using different measurements of past innovations. Also, as human capital is slow-moving indicator, we dropped this index and re0estimated all the previous estimations, but we did not observe any major changes in our main findings.

[18]We could not do the same exercise with lagged distance weighted democracy as it was not statistically a valid instrument.

[19]We also repeated the same exercise for our patent data set, but it was almost similar to our previous findings.

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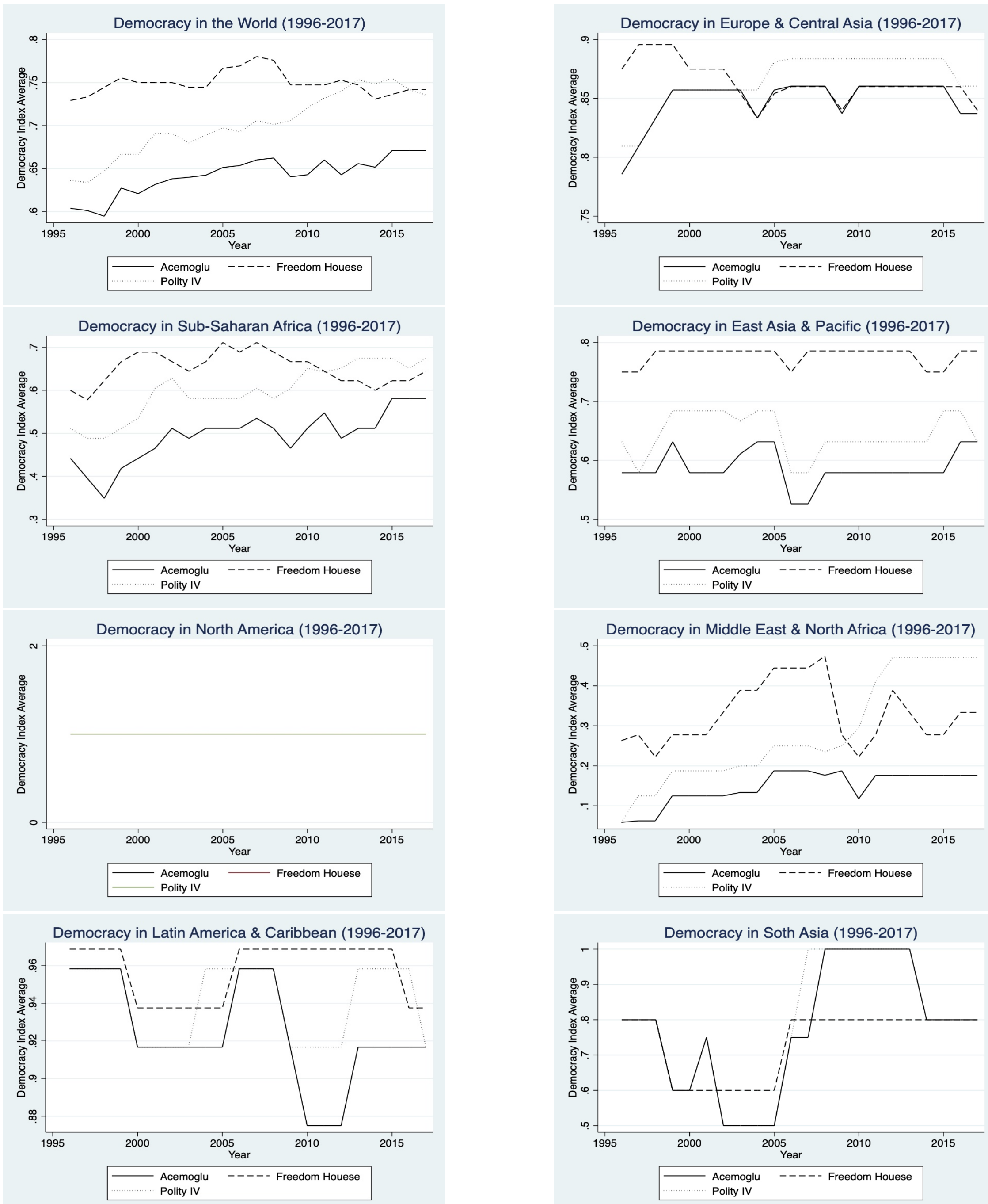
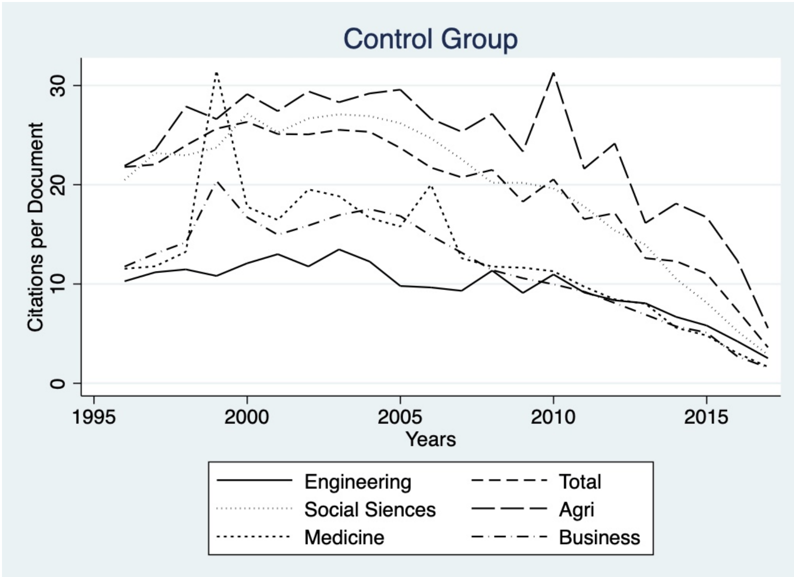
Figures and Tables

Figure 1: Democracy Measures Across Regions Over Time

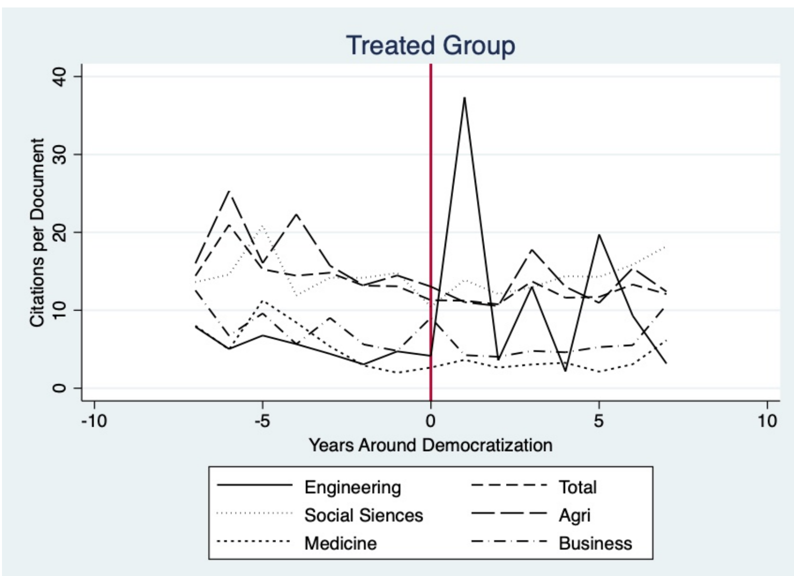


Notes: The dichotomous democracy index for non-democracies and democracies is 0 and 1, respectively. Categorization is based on the World Band definition. Source: Author's calculations based on Acemoglu et al. (2019)'s approach.

Figure 2: Average Citations Per Document in Control and Treated Coubtries



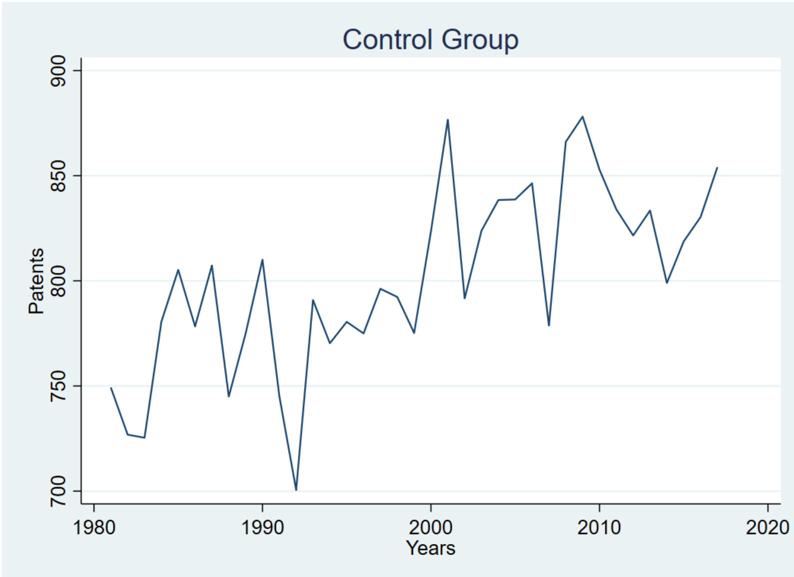
(a)



(b)

Notes: The top panel panel presents the statistics for democracies and the bottom panel presents the same statistics for non-democracies. Source: Author's calculations using SCImago data.

Figure 3: Average Number of Patents Granted in Control and Treated Couturiers



(a)

(b)

Notes: The top panel panel presents the statistics for democracies and the bottom panel presents the same statistics for non-democracies. Source: Author's calculations using WIPO data.

Table 1: Descriptive Statistics

	Democracies			***Nondemocracies***		
	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs
CPD Agriculture	18.66	15.32	2,757	15.74	14.19	1,292
CPD Arts and Humanities	17.67	40.92	2,757	15.41	41.64	1,292
CDP Bio Chemistry	24.92	22.02	2,757	20.37	20.93	1,292
CPD Bussiness	11.21	22.36	2,757	7.92	21.90	1,292
CPD Chemistry	16.64	24.25	2,757	12.75	22.96	1,292
CPD Chemical Engineering	14.92	27.14	2,757	10.65	17.31	1,292
CPD Computer Science	7.51	14.87	2,757	6.43	19.87	1,292
CPD Decision Science	8.94	15.26	2,757	6.98	15.87	1,292
CPD Dentistry	10.85	16.81	2,757	6.75	12.73	1,292
CPD Earth Sciences	18.80	21.50	2,757	14.92	20.24	1,292
CPD Economics	11.19	16.78	2,757	8.02	15.34	1,292
CPD Energy	10.65	13.57	2,757	8.73	12.97	1,292
CPD Engineering	8.59	9.63	2,757	7.74	13.03	1,292
CPD Environmetal Sciences	19.84	19.06	2,757	16.30	20.63	1,292
CPD Health	10.56	15.27	2,757	6.81	13.98	1,292
CPD Immunology	24.21	26.12	2,757	19.73	18.35	1,292
CPD Material Sciences	10.71	12.44	2,757	8.78	10.31	1,292
CPD Mathematics	7.18	9.18	2,757	6.43	14.55	1,292
CPD Medicine	23.06	21.28	2,757	18.95	34.58	1,292
CPD Multidisciplinary	65.23	111.80	2,757	35.16	126.49	1,292
CPD Neuroscience	17.52	20.62	2,757	11.48	18.36	1,292
CPD Nursing	14.70	23.40	2,757	10.49	18.97	1,292
CPD Pharmacology	17.21	17.38	2,757	15.19	17.91	1,292
CPD Psychology	15.77	54.00	2,757	13.08	37.21	1,292
CPD Physics	12.62	13.65	2,757	9.42	14.72	1,292
CPD Total	19.49	14.62	2,757	15.63	16.44	1,292
CPD Veterinary	10.14	12.68	2,757	10.13	13.42	1,292
CPD Social Sciences	10.58	12.88	2,757	9.38	17.36	1,292
Patents	775.28	490.97	3,168	624.43	515.77	2,338
Human Capital	2.63	0.68	2,076	2.04	0.56	886
Tertiary Education	38.19	27.52	1474	18.43	20.59	698
GDP per Capita	$15,709	$14,577	2,400	$11,947	$19,956	1,080
No. People Engaged	15.20	49.13	2,362	24.05	106.83	1,080

Notes: The table shows the summary statistics of the citation, patent, and other control variables. CPD stands for "citation per document" and is calculated by dividing the number of citations by number of documents. GDP per capita is in constant $US 2010, openness is measured by real exports and imports as percentage of GDP. The data for population, human capital, and the number of persons engaged in labor market are from the Penn World Tables (PWT 9.1). The data for tertiary education comes from the World Development Indicators (2019).

Table 2: Baseline Regression Results

	(1) Total	(2) Total	(3) Total	(4) Total	(5) Total	(6) Total	(7) Total
Democracy	0.026	0.042					
	(0.040)	(0.039)					
polity2			0.007*				
			(0.004)				
Civil Liberties				-0.007			
				(0.012)			
Political Rights					-0.004		
					(0.009)		
Polity IV(Dummy)						0.038	
						(0.037)	
Freedom House(Dummy)							-0.002
							(0.030)
Knowledge Stock	0.175***	0.295***	0.294***	0.279***	0.279***	0.295***	0.279***
	(0.065)	(0.043)	(0.042)	(0.043)	(0.043)	(0.043)	(0.043)
GDP Per Capita	0.083	0.055	0.052	0.040	0.041	0.057	0.042
	(0.050)	(0.038)	(0.037)	(0.037)	(0.037)	(0.033)	(0.034)
Human Capital		0.061	0.047	0.062	0.064	0.050	0.066
		(0.221)	(0.221)	(0.220)	(0.218)	(0.220)	(0.219)
Openness		-0.236**	-0.229**	-0.301***	-0.300***	-0.234***	-0.301***
		(0.091)	(0.090)	(0.091)	(0.091)	(0.089)	(0.090)
People Engaged		0.110	0.106	0.120	0.117	0.110	0.117
		(0.088)	(0.090)	(0.089)	(0.088)	(0.089)	(0.088)
Observations	3,001	2,673	2,673	2,806	2,806	2,673	2,806
Country FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
No. Countries	144	128	128	134	134	128	134
R2	0.654	0.770	0.770	0.749	0.749	0.769	0.749

Notes: The dependent variable is the natural logarithm of total number of citations per document. Democratization is constructed using Acemoglu et al. (2019)'s approach. All other independent variables are in the natural logarithm. All estimations include year and country fixed effects, and a constant term, but we do not report the results here. The asterisks ***,**, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 3: The Effects of Democratization on Citations: Heterogeneity by Field

	(1) Total	(2) Engineering	(3) Social Sciences	(4) Agriculture	(5) Business	(6) Medical	(7) Total	(8) Engineering	(9) Social Sciences	(10) Agriculture	(11) Business	(12) Medical
Democracy	0.026	0.104	0.155*	-0.039	0.151*	0.051	0.042	0.065	0.155**	0.011	0.138	0.076
	(0.040)	(0.082)	(0.093)	(0.082)	(0.087)	(0.057)	(0.039)	(0.076)	(0.078)	(0.065)	(0.088)	(0.062)
GDP Per Capita	0.083	-0.102	0.006	-0.100*	0.255**	0.169**	0.055	-0.213*	0.044	-0.036	0.288**	0.142**
	(0.050)	(0.101)	(0.107)	(0.057)	(0.115)	(0.066)	(0.038)	(0.112)	(0.127)	(0.045)	(0.142)	(0.062)
Human Capital							0.060	0.858	-0.225	-1.052***	-0.129	-0.419
							(0.221)	(0.538)	(0.541)	(0.361)	(1.009)	(0.374)
Openness							-0.236**	-0.183	-0.722***	-0.357**	-0.480	-0.448***
							(0.091)	(0.228)	(0.229)	(0.153)	(0.389)	(0.122)
People Engaged							0.110	0.427***	0.490***	0.279***	0.319	0.107
							(0.088)	(0.158)	(0.131)	(0.090)	(0.302)	(0.138)
Observations	3,001	3,001	3,001	3,001	3,001	3,001	2,673	2,673	2,673	2,673	2,673	2,673
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. Countries	144	144	144	144	144	144	128	128	128	128	128	128
R2	0.654	0.125	0.308	0.526	0.141	0.404	0.770	0.169	0.389	0.629	0.157	0.524

Notes: The dependent variable is the natural logarithm of total number of citations per document. Democratization is constructed using Acemoglu et al. (2019)'s approach. All other independent variables are in the natural logarithm. All estimations include year and country fixed effects, and a constant term, but we do not report the results here. The asterisks ***,**, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 4: The Effects of Democratization on Citations: Heterogeneity by Field

	(1) Total	(2) Engineering	(3) Social Sciences	(4) Agriculture	(5) Business	(6) Medical	(7) Total	(8) Engineering	(9) Social Sciences	(10) Agriculture	(11) Business	(12) Medical
Second Stage												
Democracy	0.576**	1.537**	2.553***	1.026**	2.200***	0.726*	0.345*	1.369**	1.888**	0.807**	2.167***	0.317
	(0.201)	(0.690)	(0.867)	(0.407)	(0.764)	(0.409)	(0.284)	(0.639)	(0.759)	(0.342)	(0.783)	(0.298)
GDP Per Capita	0.103	-0.053	0.095	-0.0598	0.326*	0.197**	0.062	-0.187	0.087	-0.015	0.336	0.149**
	(0.046)	(0.133)	(0.184)	(0.082)	(0.177)	(0.085)	(0.063)	(0.142)	(0.187)	(0.073)	(0.211)	(0.068)
Human Capital							-0.025	0.549	-0.682	-1.300***	-0.655	-0.512
							(0.251)	(0.687)	(0.713)	(0.439)	(1.201)	(0.392)
Openness							-0.198*	-0.0147	-0.529	-0.256	-0.222	-0.419***
							(0.114)	(0.300)	(0.362)	(0.223)	(0.501)	(0.133)
People Engaged							0.096	0.361**	0.424***	0.243***	0.223	0.097
							(0.096)	(0.156)	(0.157)	(0.094)	(0.307)	(0.142)
First Stage												
First-lagged Z	0.477***	0.479***	0.496***	0.496***	0.480***	0.477***	0.520***	0.525***	0.512***	0.526***	0.524***	0.520***
	(0.119)	(0.118)	(0.116)	(0.120)	(0.119)	(0.140)	(0.139)	(0.139)	(0.140)	(0.140)	(0.140)	(0.140)
Observations	2,975	2,975	2,975	2,975	2,975	2,975	2,975	2,676	2,676	2,676	2,676	2,676
KP F-Stat	16.009	16.286	16.259	17.005	16.17	15.907	15.54	15.77	15.37	15.6	15.59	15.31
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. Countries	144	144	144	144	144	144	144	127	127	127	127	127

Notes: The dependent variable is the natural logarithm of the number of citations per document in each filed. Democratization is constructed using Acemoglu et al. (2019)'s approach. All other variables are in the natural logarithm. All estimations in the second-stage regressions include country and year fixed effects, and a constant term, but we do not report the results here. The instrument for democratization is the first lag of the constructed instrument. All exogenous variables in the second-stage regression are also included in the first-stage regressions, but we do not report the results here. The asterisks ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 5: The Effects of Democratization on Patents

	(1) Patents	(2) Patents	(3) Patents	(4) Patents	(5) Patents	(6) Patents	(7) Patents
Polity IV	-0.005						
	(0.003)						
Civil Liberties		0.024*					
		(0.014)					
Political Rights			0.014				
			(0.010)				
Polity IV Dummy				-0.031			
				(0.035)			
Freedom House D					-0.040		
					(0.039)		
Democracy						-0.0240	-0.195
						(0.040)	(0.142)
							(0.118)
Knowledge Stock	0.299***	0.305***	0.305***	0.300***	0.306***	0.300***	0.294***
	(0.031)	(0.030)	(0.029)	(0.031)	(0.029)	(0.031)	(0.030)
Human Capital	0.302	0.192	0.175	0.288	0.175	0.276	0.111
	(0.227)	(0.212)	(0.214)	(0.226)	(0.213)	(0.228)	(0.340)
GDP per Capita	-0.049	-0.046	-0.047	-0.050	-0.050	-0.044	-0.048
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Openness	0.142	0.117	0.115	0.149	0.118	0.149	0.089
	(0.137)	(0.127)	(0.126)	(0.138)	(0.127)	(0.135)	(0.142)
People Engaged	0.059	0.052	0.060	0.062	0.063	0.063	0.078
	(0.087)	(0.082)	(0.081)	(0.086)	(0.079)	(0.086)	(0.085)
First Stage							
First-lagged Z							0.745***
							(0.095)
Observations	4,523	4,897	4,897	4,523	4,897	4,523	4,486
KP F-Stat Stat							60.796
Year FE	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y
No. Countries	129	140	140	129	140	129	129
R2	0.110	0.111	0.111	0.109	0.110	0.109	

Notes: The dependent variable is the natural logarithm of the number of patents granted. Democratization is constructed using Acemoglu et al. (2019)'s approach. All other variables are in the natural logarithm. All Estimations in columns 1-6 and the estimation in the second-stage regression include country fixed and time fixed effects, and a constant term, but we do not report the results here. The instrument for democratization is the first lag of the constructed instrument. All exogenous variables in the second-stage regression are also included in the first-stage regressions, but we do not report the results here. The asterisks ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 6: The Effects of Democratization on Citations Without Self-Citations: Heterogeneity by Field

	(1) Total	(2) Engineering	(3) Social Sciences	(4) Agriculture	(5) Business	(6) Medicine
Democracy	0.325	1.376**	1.972***	0.833**	2.279***	0.304
	(0.203)	(0.641)	(0.759)	(0.342)	(0.777)	(0.297)
Human Capital	-0.047	0.211	-0.777	-1.193***	-0.819	-0.530
	(0.253)	(0.705)	(0.718)	(0.402)	(1.248)	(0.393)
GDP per Capita	0.060	-0.150	0.130	-0.006	0.293	0.154**
	(0.041)	(0.139)	(0.179)	(0.070)	(0.193)	(0.068)
Openness	-0.198*	-0.153	-0.437	-0.338*	-0.726*	-0.536***
	(0.119)	(0.312)	(0.373)	(0.180)	(0.437)	(0.166)
People Engaged	0.100	0.370**	0.458***	0.194*	0.207	0.099
	(0.091)	(0.149)	(0.148)	(0.100)	(0.310)	(0.150)
Observations	2,676	2,676	2,676	2,676	2,676	2,676
KP F-Stat	15.55	15.764	15.334	15.556	15.582	15.309
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
No. Countries	127	127	127	127	127	127

Notes: The dependent variable is the natural logarithm of the number of citations per document in each filed. Democratization is constructed using Acemoglu et al. (2019)'s approach. All other variables are in the natural logarithm. All estimations in the second-stage regressions include country and year fixed effects, and a constant term, but we do not report the results here. The instrument for democratization is the first lag of the constructed instrument. All exogenous variables in the second-stage regression are also included in the first-stage regressions, but we do not report the results here. The asterisks ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 7: The Effects of Democratization on Citations with Alternative Measure of Human Capital: Heterogeneity by Field

	(1) Total	(2) Engineering	(3) Social Sciences	(4) Agriculture	(5) Business	(6) Medicine
Democracy	0.448	0.555	2.122**	1.381**	2.151**	0.168
	(0.419)	(0.715)	(0.949)	(0.588)	(0.970)	(0.482)
Tertiary Education	0.003	0.046**	-0.003	0.019	0.051*	-0.0100
	(0.012)	(0.020)	(0.022)	(0.019)	(0.029)	(0.011)
GDP per Capita	0.178**	0.145	0.219	0.013	0.598***	0.283***
	(0.084)	(0.151)	(0.168)	(0.120)	(0.206)	(0.086)
Openness	-0.352**	-0.240	-0.089	0.176	-0.440	-0.453*
	(0.149)	(0.304)	(0.331)	(0.250)	(0.429)	(0.246)
People Engaged	0.064	0.213	0.429***	0.165**	0.286	0.057
	(0.110)	(0.131)	(0.130)	(0.079)	(0.241)	(0.120)
Observations	2,005	2,005	2,005	2,005	2,005	2,005
KP F-Stat Stat	12.369	12.314	11.707	12.432	12.136	12.034
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
No.Countries	134	134	134	134	134	134

Notes: The dependent variable is the natural logarithm of the number of patents granted. Democratization is constructed using Acemoglu et al. (2019)'s approach. All other variables are in the natural logarithm. All Estimations in columns 1-6 and the estimation in the second-stage regression include country fixed and year fixed effects, and a constant term, but we do not report the results here. The instrument for democratization is the first lag of the constructed instrument. All exogenous variables in the second-stage regression are also included in the first-stage regressions, but we do not report the results here. The asterisks ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 8: The Effects of Democratization on Citations: Removing Outliers

	(1) Total	(2) Engineering	(3) Social Sciences	(4) Agriculture	(5) Business	(6) Medicine
Democracy	-0.008	0.024	0.095***	-0.047***	0.111**	0.016
	(0.014)	(0.036)	(0.035)	(0.018)	(0.048)	(0.024)
Human Capital	0.143	0.341*	-0.627**	-0.070	-0.541	0.014
	(0.107)	(0.176)	(0.240)	(0.137)	(0.471)	(0.165)
Openness	-0.099**	-0.443***	-0.084	-0.143**	-0.18	-0.060
	(0.048)	(0.089)	(0.113)	(0.065)	(0.126)	(0.068)
People Engaged	-0.035	0.0220	0.153***	0.065	0.150	0.012
	(0.043)	(0.053)	(0.058)	(0.046)	(0.127)	(0.101)
GDP per Capita	0.040*	-0.010	0.057	0.022	0.272***	0.104***
	(0.023)	(0.030)	(0.045)	(0.029)	(0.076)	(0.034)
Observations	2,571	2,371	2,509	2,552	2,523	2,582
F Stat	0.000	0.000	0.000	0.000	0.000	0.000
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
No. Countries	127	127	127	127	127	127
R2	0.964	0.934	0.873	0.953	0.900	0.922

Notes: The dependent variable is the natural logarithm of the number of citations per document in each filed. Democratization is constructed using Acemoglu et al. (2019)'s approach. All other variables are in the natural logarithm. All estimations include country and year fixed effects, and a constant term, but we do not report the results here. The asterisks ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 9: The Effects of Democratization on Citations: Removing Outliers

	(1) Total	(2) Engineering	(3) Social Sciences	(4) Agriculture	(5) Business	(6) Medicine
Democracy	0.007	0.104*	0.183***	-0.0203	0.159*	0.002
	(0.020)	(0.053)	(0.067)	(0.026)	(0.080)	(0.027)
Human Capital	-0.091	0.585	-0.577	-0.489**	-0.496	-0.369
	(0.166)	(0.438)	(0.363)	(0.206)	(0.798)	(0.225)
Openness	-0.180**	-0.495***	-0.667***	-0.171*	-0.662***	-0.216**
	(0.078)	(0.154)	(0.215)	(0.091)	(0.214)	(0.101)
People Engaged	0.071	0.246**	0.356***	0.130**	0.374*	0.134
	(0.079)	(0.100)	(0.098)	(0.065)	(0.216)	(0.133)
GDP per Capita	0.067**	-0.032	0.068	0.002	0.343***	0.093**
	(0.031)	(0.073)	(0.077)	(0.035)	(0.131)	(0.045)
Observations	2,554	2,508	2,513	2,565	2,522	2,564
F Stat	0.000	0.000	0.000	0.000	0.000	0.000
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
No. Countries	127	127	127	127	127	127
R2	0.914	0.466	0.674	0.876	0.366	0.806

Notes: The dependent variable is the natural logarithm of the number of citations per document in each filed. Democratization is constructed using Acemoglu et al. (2019)'s approach. All other variables are in the natural logarithm. All estimations include country and year fixed effects, and a constant term, but we do not report the results here. The asterisks ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 10: The Effects of Democratization on Patents: Robustness Checks

	(1) Patents	(2) Patents	(3) Patents	(4) Patents
Democracy	-0.024	-0.018	-0.030	-0.001
	(0.040)	(0.040)	(0.003)	(0.031)
Knowledge Stock	0.300***	0.277***	0.976***	0.472***
	(0.031)	(0.041)	(0.004)	(0.027)
Human Capital	0.276	-0.027	-0.009	0.173
	(0.228)	(0.018)	(0.018)	(0.181)
GDP per Capita	-0.044	-0.053	0.002	-0.040
	(0.040)	(0.046)	(0.004)	(0.026)
Openness	0.149	0.057	0.019	0.025
	(0.135)	(0.156)	(0.012)	(0.098)
People Engaged	0.063	0.102	0.002	0.036
	(0.09)	(0.115)	(0.008)	(0.061)
Observations	4,523	2,842	3,275	4,162
F Stat	0.000	0.000	0.000	0.000
Year FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
No. Countries	130	129	129	129
R2	0.110	0.096	0.997	0.334

Notes: The dependent variable is the natural logarithm of the number of patents granted. Democratization is constructed using Acemoglu et al. (2019)'s approach. All other variables are in the natural logarithm. All Estimations include country and year fixed effects, and a constant term, but we do not report the results here. The asterisks ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 11: Diffusion Patterns of Democracy

	(1)	(2)	(3)	(4)	(5)
Lagged democracy	0.713***	0.715***	0.712***	0.715***	0.713***
	(0.033)	(0.032)	(0.034)	(0.033)	(0.034)
Lagged regional democracy	0.020			0.007	0.017
	(0.045)			(0.048)	(0.049)
Lagged distance-weighted democracy		0.263**		0.259**	
		(0.123)		(0.130)	
Lagged neighbors' average democracy			0.070		0.051
			(0.194)		(0.210)
Observations	3,131	3,155	3,155	3,131	3,131
No. Countries	154	149	149	149	149
R2	0.520	0.524	0.524	0.524	0.524

Notes: The dependent variable the democratization index constructed using Acemoglu et al. (2019)'s approach. All estimations include country and year fixed effects, and a constant term, but we do not report the results here. The asterisks ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 12: Diffusion Patterns of Unrest

	(1)	(2)	(3)	(4)	(5)
Lagged unrest	0.229***	0.200***	0.201***	0.199***	0.199***
	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)
Lagged regional unrest	0.275***			0.060	0.111
	(0.051)			(0.070)	(0.070)
Lagged distance-weighted unrest		0.584***		0.515***	
		(0.133)		(0.141)	
Lagged neighbors' average unrest			0.107***		0.090***
			(0.029)		(0.031)
Observations	5,101	3,271	3,271	3,269	3,269
No. Countries	233	150	150	150	150
R2	0.181	0.216	0.214	0.216	0.216

Notes: The dependent variable the unrest index reported by CNTS. All estimations include country and year fixed effects, and a constant term, but we do not report the results here. The asterisks ***, **,and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.

Table 13: The effects of Democratization on Citations: Alternative IV Approach

	(1) Total	(2) Engineering	(3) Agriculture	(4) Social Sciences	(5) Business	(6) Medicine
Second Stage						
Democracy	0.342***	0.559	0.574*	0.887***	0.834**	0.119
	(0.122)	(0.348)	(0.314)	(0.301)	(0.349)	(0.144)
Human Capital	-0.0278	0.930	-1.087***	-0.224	-0.00175	-0.404
	(0.249)	(0.577)	(0.410)	(0.569)	(1.069)	(0.395)
GDP per Capita	0.061	-0.197	-0.017	0.097	0.311*	0.126**
	(0.045)	(0.120)	(0.065)	(0.148)	(0.162)	(0.061)
Openness	-0.204*	-0.138	-0.332	-0.621**	-0.393	-0.441***
	(0.116)	(0.257)	(0.219)	(0.289)	(0.435)	(0.128)
People Employed	0.0937	0.368**	0.215**	0.439***	0.277	0.139
	(0.095)	(0.156)	(0.092)	(0.138)	(0.311)	(0.135)
First Stage						
First-lagged Z	3.404***	3.406***	3.406***	3.379***	3.404***	3.395***
	(0.478)	(0.481)	(0.469)	(0.477)	(0.478)	(0.481)
Observations	2,596	2,596	2,596	2,596	2,596	2,596
KP F-Stat	49.602	50.788	49.985	51.998	50.886	50.437
Year FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
No. Countries	127	127	127	127	127	127

Notes: The dependent variable is the natural logarithm of the number of citations per document in each filed. Democratization is constructed using Acemoglu et al. (2019)'s approach. All other variables are in the natural logarithm. All estimations in the second-stage regressions include country fixed effects, year dummies, and a constant term, although we do not report the results here. The instrument for democratization is the first lag of the constructed instrument, based on the level of democracy in neighboring countries. All exogenous variables in the second-stage regression are also included in the first-stage regressions, but we do not report the results here. The asterisks ***, **, and * indicate the 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are robust standard errors clustered at the country level.