Nature as Patronage?

Exploring The Effects of Democratization and Support Coalition Identity on Forest Loss

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Abstract

Can democratization have an adverse effect on forests? As deforestation presents one of humanity's most pressing environmental challenges in effort to limit global climate change, understanding the effects of political institutions on forest loss is of importance. In this thesis I re-investigate the findings of Sanford (2021) and others suggesting that democratization is associated with deforestation in young democracies due to increased political competition. Leveraging satellite measurements of forest cover aggregated into 0.5° grid cell panel data from 1982 to 2016, as well as data on regimes' political support bases (support coalitions), I explore whether the effect of democracy on forest cover change is moderated by the identity of the key support groups that the post-transition regime needs to stay in power. Drawing on existing literature, I theorize that different support coalition identities (urban and rural coalitions) reflect different economic and political interests in society, which in turn could affect environmental outcomes such as deforestation.

In order to explore these relationships, I used OLS with two-way fixed effect as well as Mahalanobis distance matching with panel data. I find that the associated effect of democracy on forest loss is heterogeneously moderated by support coalition identity and forest type, with democratic regimes interacted with rural supporters being associated with an average increase in forest cover globally (reforestation). Moreover, neither democracy nor its interaction with different support coalitions had an effect on a tropical forest sub-sample. I further probe for the total effect of different support coalitions on forest cover change, regardless of regime type. From this analysis, I find that regimes who rely on the support from urban groups are associated with higher-than-average forest loss across global forest and in the tropics. I argue that these findings imply that the effect of democratization varies across different contexts, and that more attention should be given to the idiosyncratic support bases of incumbent/new regimes to better understand the dynamics of political deforestation.[1]

[1] My R scripts can be downloaded from https://github.com/jens-koning, or received by contacting jens.jjk@gmail.com. Any mistakes are my own.

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*The world is changing. The planet is heating up. What the f*ck is going on?*
- Bo Burnham, from the song *Comedy*.

These have been two wild years to do a master's degree. Yet here I am, at the end. The job's done. I could not have done it without the company and support of so many amazing people. First and foremost, I would like to thank my supervisors - Marina Povitkina and Carl Henrik Knutsen - for their excellent guidance throughout this last year, and for pushing me across the finish line. Marina, thank you for your encouragement and for pointing me in the direct of studying deforestation, it has been quite the journey. Carl Henrik, thank you for your on-point comments and impressively quick replies whenever I encountered a problem. You guys are great!

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- *Jens Koning, Oslo, May 22. 2022*

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Chapter 1

Introduction

In May 1998, Indonesia's long-ruling dictator - Haji Mohamed Suharto - resigned from political office following several days of country-wide mass protests against the *Golkar* regime. Suharto's resignation marked the end of 31 years of autocratic rule in Indonesia and the beginning of *reformasi* (reform and democratization), culminating in the country's first direct presidential election in 2004. Since 1998, Indonesia's has drastically improved civil liberties, held increasingly competitive elections and quadrupled its gross domestic product (GDP) per capita. However, in contrast to these achievements, Indonesia has also seen extensive environmental degradation, especially in its tropical rain forests. Multiple studies find evidence for extensive logging and land clearing during electoral cycles in Indonesia, and has linked this to politicians seeking stay in political office (Austin et al. 2019; Cisneros et al. 2021; Tsujino et al. 2016). Similar patterns of deforestation have been documented following transitions to democracy in other developing and middle-income countries such as Kenya and Brazil, suggesting that this might be a global phenomenon (Klopp 2012; Pailler 2018). These observations raise the question of whether democratization can be linked to deforestation as political competition increases.

As loss of intact forests caused by human activity is one of the most pressing environmental challenges of our time, understanding the effect of political institutions on forests is of importance. Deforestation exacerbates global climate change by releasing carbon dioxide (CO_2) into the Earth's atmosphere, reduces biodiversity by destroying natural habitats and increases the likelihood of future zoonotic pandemics (Bala et al. 2007; Gibbs et al. 2010; Gibb et al. 2020; Lawrence and Vandecar 2015).[1] Recent estimates suggest that 60% of deforested intact forests between 1982 and 2016 is caused by direct human activity such as the creation of new agricultural land driven by increased global demand for food, livestock feed and fuel, while the remaining 40% being due to indirect drivers such as climate change (Curtis et al. 2018; Song et al. 2018, p. 639). While the global rate of deforestation has been slowing in recent decades, it has also *accelerated* in tropical lati-

[1] Findings from Alkama and Cescatti (2016) suggests that deforestation accounts for over one third of all greenhouse gas emissions (GHGs).

tudes, where forests play a particularly important role in managing global temperatures through precipitation frequencies (Song et al. 2018; Lawrence and Vandecar 2015). As such, furthering our understanding of the political determinants of deforestation can help prescribe better policy recommendations to mitigate deforestation, but also to further our understanding of the dynamics of what Jagers et al. (2019) call *large-scale collective action problems*.[2] Doing so also contributes to understanding how to prevent *future* damage by ensuring that the environmental problem does not surpass so-called 'tipping points' – conditions where ecological systems lose their resilience (Lenton et al. 2008).

As about 90% of forests globally are located on publicly owned land (Malhi et al. 2008), deforestation is a political problem that can be affected by political institutions. In the existing political science literature, a growing body of empirical evidence supports the claim that democracies on average tend to outperform autocracies across a variety of environmental indicators (e.g. Bernauer and Koubi 2009; Gleditsch and Sverdrup 2002; Li and Reuveny 2006; Sjöstedt and Jagers 2014; Stein 2020; Wurster 2013), with a few exceptions (Buitenzorg and Mol 2011; Midlarsky 1998; Sanford 2021). These exceptions have in common that they all emphasize that democracy's relationship with *forests* may be more convoluted than for other environmental indicators.

In a recent study representing this discussion, Sanford (2021) uses satellite aggregated panel data to argue that countries that experience a democratic transition are associated with higher rates of deforestation under democracy than autocracy. The purposed mechanism driving this effect is the short-time horizon and clientalistic political relationships of politicians in young democracies (Keefer 2007), which makes forests a 'distributive good' suitable to garner political support (Albertus 2017). However, could this effect be moderated by the *types* of support bases that the incumbent politicians rely on to stay in power? Both Sanford (2021) and Stein (2020) mention the influence of political supporters on candidates, with Sanford noting that "[p]oliticians choose to allow, induce, or even subsidize deforestation to garner political support when they fear they might not be re-elected" (Sanford 2021, p 14). I identify that these observation have some theoretical overlap with theory on the behavior of *support coalitions* (Bueno de Mesquita, Smith, Siverson, et al. 2003; Wig, Dahlum, Knutsen, et al. 2020), and suggest that the specific characteristics of a regime's support coalition, i.e. the identity of the key support groups needed by the incumbent regime to remain in power,[3] may reflect different economic and political interests in society which could affect environmental outcomes such as deforestation. Therefore, this thesis seeks to address the following general research question:

[2] Such as climate change, pandemics, oceanic microplastic pollution or transnational air pollution.

[3] 'Regime' is defined as the rules that are essential for selecting political leaders and for maintaining them in power. See Chapter 2.1 for definition of the concepts.

Does the identity of a regime's supporters moderate the effect of democracy on deforestation?

Specifically, I will investigate whether the effect of democratization on deforestation, a country's transition from autocracy to democracy, is moderated by the identity of the post-transition support coalition. Building on previous studies (Sanford 2021), I argue that this question can be explored with existing data. Further, using a large-N design also has the potential to draw generalizable conclusions and is the only method to determine whether a relationship is systematic across multiple countries and time periods. By addressing the potential heterogeneity of individual countries' institutions, I seek to contribute by offering insights on the informal characteristics of individual regimes. To do this, I leverage a global data set of forest cover change by Song, Hansen and Stehman, et al. (2018) aggregated into 0.5° grid cell panel data from 1982 to 2016, as well as data covering the characteristics of individual regimes' support coalitions by Coppedge, Gerring, Knutsen, et al. (2021). Drawing on existing literature, I theorize that the interests of four different support groups - *rural supporters*, *urban supporters*, *agrarian elites* and *business elites* - reflect distinct economic and political interests in a given society that can effect forests in a new democracy. Additionally, to further elucidate the role of regime support groups, I probe for the total effect that these support groups have, regardless of regime type. As deforestation as global policy issue is relatively recent, starting in the 1970s and becoming increasingly relevant,[4] I argue that 1982 is an appropriate year for studying the research question. With a data set starting in 1982, I am able to capture most of Huntington's (1992) 'third wave' of democratization as well as new democracies in the 2000s, offering global coverage on the potential heterogeneous effects of democracy.

To investigate these relationships, I use a set of two-way fixed effect (TWFE) models as well as Mahalanobis distance matching for some of the robustness checks. I find that when rural supporters are in the incumbent regime's support coalition, the marginal effect of democracy on forest is positive, meaning that these democracies were associated with *reforestation* (more forest). When interacting democracy with the the other support groups, democracy does not have a significant effect on forest forest change across my global forest sample. Interestingly, neither democracy, nor democracy interacted with the different support groups had a statistically significant effect on my tropical forest sub-sample. This is surprising given that the case-study literature on democracy and deforestation often focuses on countries in the 'tropical belt.' When probing for the total effect of different support coalitions on forest change (assuming that the effect is equal for democracies and autocracies), I find that when urban supporters are present in the support coalition, deforestation on average increases across global forests, as well as for

[4] As illustrated with the global forest finance pledge during the United Nations Climate Conference in 2021 (Conference of the Parties 26/COP 26).

the sub-sample of tropical forests. I argue that these findings imply that the effect of democracy varies across different contexts, and that additional insights can be revealed by studying the idiosyncratic support bases of incumbent or new regimes.

1.1 Structure

Following this first introductory chapter, the thesis is structured as follows. In chapter 2, I outline the central concepts that will be used in this thesis, discussing their definitions. I then move on to review the existing literature on deforestation, outlining three drivers of deforestation; (1) natural drivers, (2) economic drivers and (3) political drivers. One of the main takeaways from this chapter is the potential influence that different political support bases may have on deforestation. Chapter 3 outlines the theoretical framework I use in this thesis. Here, I first discuss the relative political value of forests for both incumbent politicians as well as voters/citizens. Then, I outline how clientalistic politics in young democracies may exacerbate deforestation, as theorized by Sanford (2021) and others. From there, I synthesize these observations with theory on different regimes' support coalitions, and their unique interests in forested land. In chapter 4, I present and discuss the data that I use, as well as issues related to reliability and measurement validity. Further, I describe the statistical models that I use in this thesis and their assumptions. In chapter 5, I first present the results from the moderation analysis, testing whether support coalition identity moderates the effect of democracy on forest loss. I then probe further, testing the total effect that these groups have on forest change, regardless of regime type. I proceed by running various robustness checks, and use Mahalanobis distance matching to re-test some of the main findings from the previous sections. I move on to discuss the limitations of my analysis. Lastly, in chapter 6, I discuss the implications of my findings and present a conclusion while outlining potential avenues for further research. Additional model specifications, diagnostics, and statistics can be found in the appendices that follow after the bibliography.

Chapter 2

Concepts and Literature Review

In this chapter I first outline and clarify some key central concepts used in this thesis. The second part of the chapter reviews existing literature on the drivers of deforestation to identify the knowledge gap that this thesis seeks to fill: Do heterogeneous political support groups moderate the effect of democratic institutions on forest change?

2.1 Concepts

Below I define the central concepts that I will return to in this thesis, namely *political institutions*, *regime type*, *support coalition*, *public/distributive goods* and *democracy.* These concepts are not easy to define, and can be interpreted in different ways by different scholars. The measurement of these concepts are also subject to ongoing scholarly debates, and variations in their definitions also come with different sets of assumptions. It is therefore important that I define these concepts properly, as the definitions have implications for how I seek to answer my research question, as well as for interpreting the results in the empirical analysis of this thesis.

Political institutions. I borrow North's (1990) definition of institutions as human-made constraints that shape the "rules of the game" within a polity by structuring the incentives for human exchange, whether it be political, economic or social (North 1990, p. 3). These constraints can be both formal or informal in nature. Informal constraints are norms, traditions and idiosyncratic customs, while formal constraints are legal frameworks and regulations. In tandem, these constraints shape human behavior. As such, it is widely regarded that "institutions matter" for a variety of measurable outcomes, whether it be economic development, human health, environmental quality or questions of war and peace. A remaining uncertainty is the *extent* to which institutions matter. Often these uncertainties derive from the behavioral assumptions in theories of institutions: that actors behave in according to rational choice theory and expected utility. North (1990) noted that while social scientists rarely assume that rational choice behavior *always* reflects human behaviour accurately, they still "[...] believe that such assumptions are useful for building models of market behavior in economics and, though less useful, are still the best game in town for studying politics and the other social sciences" (p. 17).[1] Taking this into consideration, as well as the complex nature of politics, I adopt a stochastic assumption of rational choice for understanding how political institutions shape the behavior of human actors.

Regime. One popular macro-measurement of political institutions is *regime type*. Schmitter and Karl (1991) define regime type as an "ensemble of patterns that determines the methods of access to the principal public offices; the characteristics of the actors admitted to or excluded from such access; the strategies that actors may use to gain access; and the rules that are followed in the making of publicly binding decisions." (Schmitter and Karl 1991, p. 76). As such, regime type alters the way in which policy preferences are aggregated. Regime type is typically operationalized as varying on a continuum from democratic to autocratic rule. In this thesis I will adopt a similar, but minimalist definition of regime based on Djuve, Knutsen and Wig (2019) as well as Geddes, Wright and Franz's (2014) definition. They define a *political regime* as the rules that are essential for selecting political leaders and for maintaining them in power. These rules can be formal, such as written in constitutions, and/or informal rules and practices, enforced by a broader or narrower group of people within a polity. The central characteristic of a regime is therefore *who selects policies*, and *how* these policies are typically selected (Djuve, Knutsen and Wig 2019, p. 927).

Support coalition and support groups. The individuals who are able to select policies (as well as alter how these policies are selected) are the enfranchised part of a political regime's population. These can be considered to be a part of what Wig, Dahlum, Knutsen and Rasmussen (2020) call a regime's *support coalition*, meaning the parts of the population that directly or indirectly enhances the survival ability of the incumbent regime. The coalition consists of one or several distinctive 'support groups', being members of within the support coalition that share a particular social identity. Example of support group identities, from farmers belonging to the rural working class, or wealthy urban business elites, or generals belonging to the military. Hence, the support coalition consists of *all* relevant support groups for the regime, at a particular point in time (Wig, Dahlum, Knutsen and Rasmussen 2020, p. 7). Given that the incumbent regime relies on the support coalition to stay in power, then the key assumption is that the support groups use their political prowess to constrain the incumbent's decision-making. Therefore, the social make-up of the coalition heterogeneously affects the incumbents decision-making contingent on the support groups particular interests.

[1] Gartzke (1999), studying war, exemplified this limitation by noting that the outbreak of war as a phenomena is often associated with the "error term" of a statistical model, namely something exogenous or unobserved (implicitly; random).

Public- and private/distributive goods. Simplified, an incumbent regime can choose to provide goods and services to society on a continuum between targeted private/distributive goods, or non-targeted public goods. Non-targeted public goods are government initiatives that are intended to benefit and be accessible to (nearly) all of a society, being non-rivalry and non-excludable. However, these are independent characteristics and can exist without the other, and they can be present in varying degrees, i.e. they are not all-or-nothing characteristics (Adams and McCormick 1993, p. 109). Targeted good private/distributive goods are utilized by incumbents as a transfer to rally political support, being analogous to a vote-buying tool (Albertus 2013, p. 1084; Keefer 2007, p. 804).

Democracy and democratization. Recognizing that democracy can be defined and measured in many different ways,[2] I adopt a 'thin' definition of democracy based on Robert Dahl's 1982 definition. Dahl noted seven distinctive qualities of procedural minimal democracy: (1) Control over government decisions about policy is constitutionally vested in elected officials; (2) elected officials are chosen in frequent and fairly conducted elections in which coercion is uncommon; (3) all adults can vote in the election of officials; (4) all adults can run for elective offices in the government; (5) citizens can express themselves about political affairs without the danger of punishment; (6) diverse forms of information about politics exists, and these sources of information exist and are protected by law; lastly, (7) citizens also can form relatively independent associations or organizations, including independent political parties and interest groups (Dahl 1982, p. 11). In this regard, *democratization* refers to the transition from autocratic rule (partially or fully lacking the above criteria), to a democratic rule that reflects the above criteria (see Chapter 4 for operationalization).

Dahl (1971) pointed out that the most important characteristics of democracy can be measured along the two dimensions of *contestation* and *inclusiveness*. Contestation denotes the extent of permissible opposition, public contestation, or political competition within a political unit, while inclusiveness denotes the proportion of the population entitled to participate on a more or less equal basis in controlling and contesting the conduct of government. If a polity scores high on both dimensions, then Dahl termed it 'polyarchy' (i.e. rule of the many). There are both advantages and drawbacks with using this 'thin' definition of democracy. A thinner definition allows for easier crowd-based assessment of what is, and what is not a democracy, as well as making it more theoretically adaptable for diverse theories. However, using a thin definition also omits many of the qualities associated with democracy, such as majority rule, separation of powers or socioeconomic equality etc. A 'thicker' definitions allows for more variation, and as such, better idiosyncratic explanation of a polity's democratic institutions, which matters when embedded in a well-defined theory (Coppedge 2012, p.21-24).

[2] Coppedge (2012) points out that democracy is a multidimensional phenomena (Coppedge 2012, p. 47).

2.2 What drives deforestation?

In this section I review the existing literature on deforestation. Deforestation is a complex process, which pertains to a myriad of different drivers such as nature, economic incentive structures as well as politics. This has led some scholars to point out that deforestation resembles something close to a *wicked problem*, being difficult to theorize universal causes of due to the interconnected and complex characteristics of the problem (McCarty and Tacconi 2011).[3] However, advancements in remote sensing such as the NASA/USGS Landsat satellite program (from 1972 to today) has contributed significantly to our current understanding of global forest change and land usage (Song, Hansen, Stehman et al. 2018). Scholars are attempting to understand what role forests have on the global environment, and model forests in complex systems. Earth System Science (ESS) have attempted to model how different natural 'spheres' of the Earth interact, originally modelling the cyclical interactions of the geosphere and biosphere (NRC/NASA 1986), including the role of forests. Since the 1990s EES scholars have sought to incorporate human impact on the biosphere and geosphere, often referred to as the anthroposphere, as humanity increasingly has an out-sized impact on the natural environment (Steffen, Richardson and Rockström et al. 2020).

I divide the purposed causes of deforestation into three different categories: (1) Natural drivers, (2) economic drivers and (3) political drivers. Drawing on the ESS perspective, I recognize that these categories are not mutually exclusive, i.e. natural drivers can affect both economic and political ones or vice versa. Yet, I argue that these categories are productive insofar they reflect different scholarly perspectives on the drivers of forest loss. As the main emphasis of this thesis is on the political drivers of deforestation, more attention will be given to these drivers (anthropogenic drivers) with particular attention being given to the literature on the purposed effects of political institutions (and democracy) on forests.

2.2.1 Natural drivers

Song, Hansen and Stehman et al. (2018) estimates that 40% of forest cover loss is driven by indirect drivers (p. 639).[4] Natural disturbances of forests, such as fires, droughts, ice, pathogens, insect outbreaks and windthrows, are all a normal part of ecosystem dynamics in forests globally (Frelich 2002; Turner 2010; White 1985). They occur as what Seidl, Thom, Kautz, et al. (2017) call "relatively discrete events", and form characteristic regimes of typical disturbance frequencies, sizes and severities that over extended spatial and temporal scales (p. 395). These disturbances disrupt the structure, composition and

[3] McCarthy and Tacconi (2011) argue that it may not be possible to outline universal macro-level explanations of forest cover as due to political and economic factors.

[4] Song et al. (2018) defines indirect drivers as both natural drivers and human-induced climate change.

function of an ecosystem, and change the resource availability or the physical environment. In turn this creates natural heterogeneity in the forested landscape, which fosters diversity across a wide range of guilds and species resulting in ecosystem renewal (Seidl, Thom, Kautz, et al. 2017).

In recent decades, however, disturbance regimes are changing in forest ecosystems with more profound forest fires, droughts and insect outbreaks (p. 395). Over time, these alterations have a significant impact on the ability of forest ecosystems to self-regulate, resulting in deforestation as forests begin to die. According to Seidl, Thom, Kautz, et al.'s (2017) meta-analysis of 674 papers (drawing on 1,699 individual disturbance events), the global increase of disturbance events are increasingly related to human-made climatic change, driven by water scarcity and rising temperatures (accounting for the primary cause of increased disturbances in 37% and 42% of the reviewed papers in Seidl, Thom, Kautz, et al. (2017) respectively). The effect of human-made climate change on deforestation therefore exemplifies how natural drivers are strongly interlinked with economic and political drivers.

2.2.2 Economic drivers

In general, evidence suggests that economic growth as a driver of deforestation (Chupezi 2009; Mertens and Lambin 1997). A prominent theory in the economic literature on environmental degradation and growth is the environmental Kuznets curve (EKC) hypothesis.[5] The EKC states that we can expect to see an inverted U-shape relationship between environmental degradation and economic growth. In this regard, the EKC predicts that deforestation will increase during the beginning of development (often measured in GDP per capita), then reach a peak and later stabilize or decrease when the country reaches a higher level of economic prosperity and no longer relies as heavily on industrial manufacturing as a key part of the economy (Stern 2018). Numerous studies have seen the EKC fit to different countries and regions, pointing to a correlational relationship between environmental performance and GDP per capita, however the fit varies widely depending on environmental pollutant, and there is still considerable uncertainty in regards to the EKC's ability to predict forest loss (Choumert et al. 2013, p. 25).[6] Moreover, the EKC hypothesis is state-centric (not taking into account transnational nature environmental problems), and offers limited insight into the idiosyncratic causal *mechanisms* of economic development on different of environmental indicators.

More precise mechanisms that link specific economic activity to deforestation are diverse,

[5] The EKC is a modified version of the original Simon Kuznet's original theory used to describe the relationship between market forces and economic inequality.

[6] For example, Apergis and Ozturk (2015) find empirical support for the EKC hypothesis across 14 Asian countries, although the "peak" of the inverted U-curve varies depending on the measured pollutant (Apergis and Ozturk 2015, p. 21

including both domestic and international factors. Domestically, many developing countries utilize forests as fuel wood for basic amenities such as cooking and heating, as well as for domestic trade of charcoal (Cline-Cole 1990; Specht et al. 2015). Extractive industries such as mining is another powerful driver of deforestation, as mining requires infrastructure establishment, urban expansion to support a growing workforce, and development of mineral commodity supply chains (Ranjan 2019; Sonter et al. 2017). Internationally, the increasing and diversifying consumer demand for agricultural products through global supply chains networks means that consumer habits outside a forested country may provide strong incentives for actors to deforest in order to create new farmland or for sale of wood (Marques 2021). A recent article by Hoang and Kanemoto (2021) quantifies the relationship between consumer demand abroad and domestic deforestation, finding that demand in developed countries drives economic incentives to deforestation in developing countries. Consumption patterns of G7 countries drives an average loss of 3.9 trees per person per year, with key hotspots for demand-led deforestation being in Southeast Asia, Madagascar, Liberia, Central America and the Amazonian rain forest (p. 845). Both case-based and cross-country evidence points towards trade openness increasing deforestation, and that tropical rain forests being particularly vulnerable (Faira and Almeida 2016; Tsurumi and Managi 2014). For example, Faria and Almeida (2016) finds that in Brazil forests are increasingly being cleared for the production of soy beans and beef cattle intended to be sold internationally, however pointing out that central-government efforts to conserve parts of the Amazon has yielded effective reductions in international demand-led deforestation - highlighting how political and economic factors are carefully intertwined.

Corruption is also regarded as a salient mechanism promoting deforestation. Corruption can be broadly defined as the abuse of entrusted power for private gain (Svensson 2005, p. 20; Transparency Intl 2021),[7] and has been shown to moderate the positive effects of democracy on different environmental indicators (for example, CO_2 emissions, Povitkina 2018a). Numerous case-based and cross-country studies also find strong associations between prevalence of low- and mid-level corruption and deforestation (for example, Barbier et al. 2005; Galinato and Galinato 2012; Koyuncu and Yilmaz 2009; Meehan and Tacconi 2017). While there have been advancements in scholars' ability to measure low- and mid-level corruption, a remaining limitation to the corruption literature and indices is the reliance on perception-based surveys of attitudes and experiences of different stakeholders in a given society (i.e. the general population, economic agents and experts),

[7] Povitkina (2018a) outlines the key mechanisms of corruption leading to worse environmental performance: "[...] Corruption obstructs the coercive power of the state in mitigating environmental problems by lowering the quality of inspections, monitoring, and the ability of the bureaucrats to effectively design and implement policies. It impedes voluntary compliance by reducing trust between the individuals and trust in government. It diminishes extractive capacity of the state, preventing higher tax revenues, which could otherwise contribute to environmental budgets." (Povitkina 2018a, p. 412).

which do not measure corruption directly (Fazekas and Kocsis 2020, p. 156; Heywood and Rose 2014, p. 507). Burgess et al. (2013), leveraging spatial panel data of forest cover change in Indonesia, also finds that rent-seeking local jurisdictions led to increases in illegal logging (and hence deforestation) as well as created lower timber prices (consistent with 'Cournot competition' - an economic model in which companies compete on the amount of output they will produce). Burgess et al. argue that local- and provincial level governments are of limited help in mitigating forest loss, and that national government measures should be enacted to stop deforestation. This observation is important, as it highlights that stopping extensive deforestation ultimately relies on the willingness of actors in central governments s to devote attention to the issue. Other studies have also supported a similar notion that delegating responsibility local jurisdictions can result in higher levels of deforestation (see for example Pailler et al. 2018). The findings in these studies carry significant implications, as halting deforestation may therefore be contingent on the policy-decisions of the incumbent central government of a country.

2.2.3 Political drivers

Cross-country evidence suggests that major disturbances or crisis, such as presence of war and political instability (such as coup d'etats), may alter rates of forest loss (see for example Didia 1997). Quasi-experimental evidence from the civil wars in Sierra Leone and Colombia suggests that war halted deforestation in areas that experiences fighting, as conflict disturbed the incentive structures and costs of local economic activity related to forests (Burgess et al. 2015, p. 9; Prem et al. 2020, p. 1). On the contrary, Butsic et al. (2015) using spatial panel data from the Democratic Republic of Congo and finds that conflict exacerbated deforestation, although conflict lessens forest loss in areas with extractive industries. In sum, while scholars are beginning to unpack the nexus between conflict, political instability and deforestation, there is still much uncertainty about the mechanisms and prevalence of this phenomena.

A more established assumption in the political science literature, is that institutions such as regime type has a measurable effect on the environment in general. A growing body of empirical evidence supports the assumption that democracies on average tend to outperform autocracies across a variety of environmental indicators (e.g. Bernauer and Koubi 2009; Gleditsch and Sverdrup 2003; Li and Reuveny 2006; Sjöstedt and Jagers 2014; Stein 2020; Wurster 2013), with a few exceptions (Buitenzorg and Mol 2011; Midlardsky 1998; Sanford 2021).[8] Given these empirical findings, what are the purposed causal mechanisms of democratic institutions that would make them improve the environment, and what are the arguments for democracy worsening the environment? In the below paragraphs I review the arguments on the general role of democracy as these are relevant for understanding the specific arguments regarding democracy's purposed mechanisms and effects on forests.

Why democracy may improve environmental quality. According to Schultz and Crockett (1990) and Payne (1995), democracies tend to have established political rights and freedom of information that promote the cause of environmental civil society (such as non-governmental organizations (ENGOs) and activists) which in turn raise public awareness about environmental problems and encourage environmental legislation. The effect works through environmental groups and public opinion at large as information on environmental issues flows more freely, and political rights are more numerous and better protected in democracies than autocracies (Li and Reuveny 2006, p. 936-37). As pointed out by McAdam (2017), Rootes, Zito and Barry (2012) and others, environmental civil society works as an important mechanism for heightening the *issue salience* of

[8] Public good provision theories hold that democracies' large support coalitions hold leaders more accountable for their actions vis-a-vis autocracies (Bueno de Mesquita et al. 2005; Lake and Baum 2001). Democracies with large support coalitions have been associated with better environmental public goods such as air quality (Cao and Ward 2016).

environmental problems.[9] Additionally, election cycles in democracies are also important in consolidating public support and legitimacy for a particular policy agenda. Kotov and Nikitina (1995) point out that as democracies tend to hold relatively free and fair elections providing the ability to bring pro-environmental political parties (green parties) to power. Indeed, Mourao (2019) finds that the higher shares of green party seats occupied in parliament tended to be observed in countries with most significant reduction in environmental pollutants (Mourao 2019, p. 985). In autocracies, however, elections are rarely free, and power is more concentrated, hampering the likelihood of green parties emerging. Elections further serves to promote both responsiveness to people's concerns about the environment and accountability for addressing these concerns (Barrett and Graddy 2000). However, the implication of this, as Li and Reuveny (2006) points out, is that people can also elect parties and politicians with anti-environmentalist agendas, although they argue that this does not empirically tend to happen (Li and Reuveny 2006, p. 937). In sum, democracy tend to foster a vibrant environmental civil society and electoral accountability which it better at mitigating environmental degradation than autocracy.

Why democracy may worsen environmental quality. Sceptics of democracy's environmental benefits present several general mechanisms. Hardin (1968) argued that individual freedoms and rights could potentially bring about unchecked natural resource exploitation by self-interested individuals and/or groups. The key problem that Hardin identifies in his essay is that property rights of specific natural resources are often not well defined, such as "the commons" (clean air, clean oceans and forests). As such, self-interested individuals or interest groups can tend to over-exploit natural resources and ignore the damage that their economic actions inflict on the environment as well as long-term collective prosperity, i.e. creating the "tragedy of the commons" (Hardin 1968, p. 162). Others, such as Dryzek (1987) have pointed to the ambiguous role of the market in democracies, as the market can both help to ensure quality of environment by managing resources more efficiently (Berge 1994), as well as facilitate powerful corporate special interest groups and labour unions that seek to hinder the cost of environmental legislation through lobbying or clientalistic relationships (Dryzek 1987, p. 121). Various case studies have shown how special interests groups can influence policy aggregation in democracies (Bättig and Bernauer 2009; Brulle 2018; Downie 2017; Meckling 2015; Mildenberger 2020; Vesa et al. 2020). Typically, these interest groups tend to be well-funded in comparison to pro-environmental groups (Brulle 2018, p. 289), work in nontransparent manners often using inside lobbying through direct consultations and hearings with policy-makers (Vesa et al. 2020, p. 7).[10] Lastly, Congleton (1992) and Midlarsky (1998) suggest that

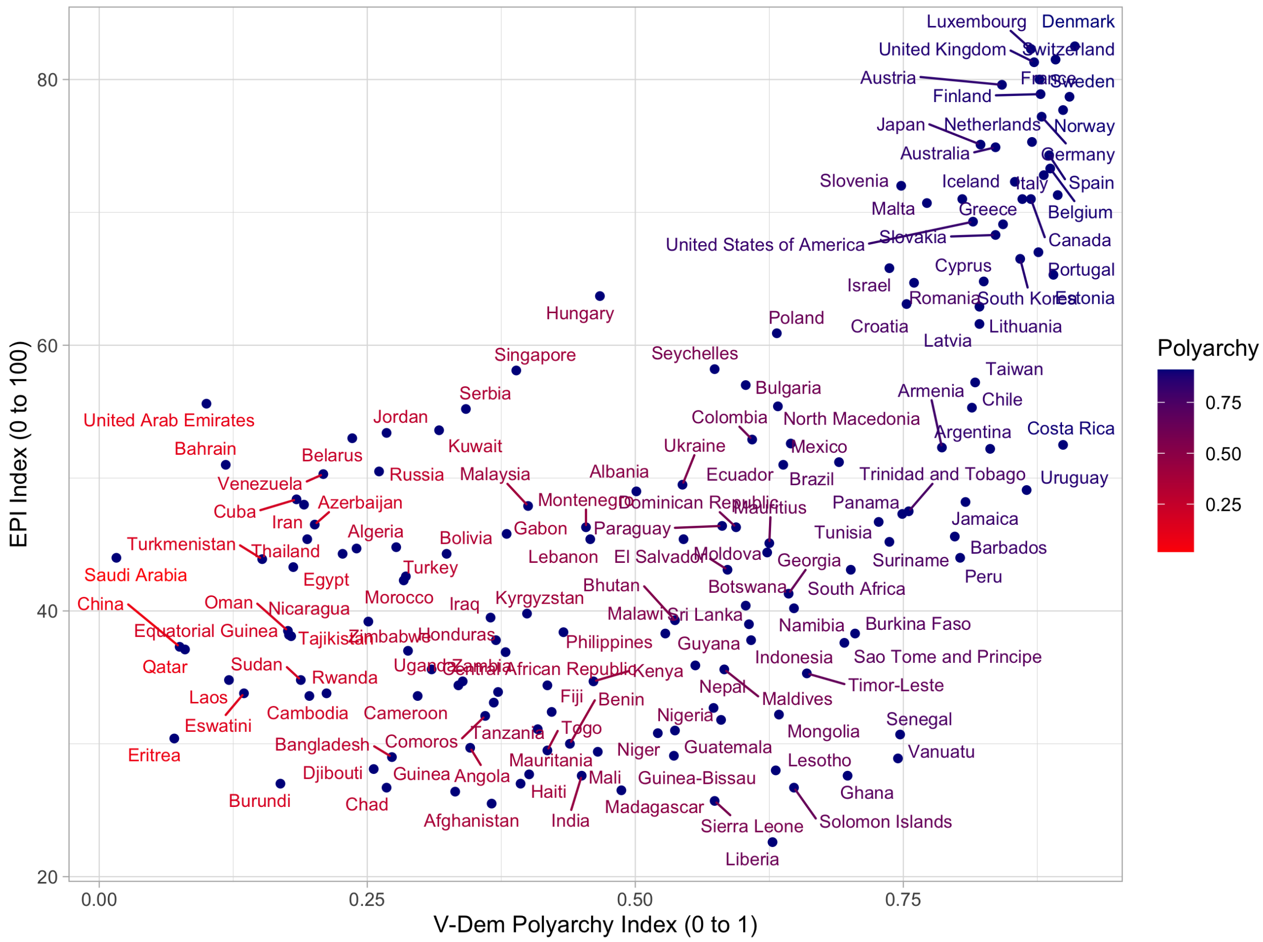
[9] Issue salience can be define as the extent to which people cognitively and behaviorally engage with a political issue (Moniz and Wlezien 2020).

[10] However, these relationships are not necessarily exclusive to democracies, and is possible that similar relationships are even more exacerbated in autocracies where ruling elites depend upon the support of such interests.

politicians in democracies have a tendency to focus on short-term electoral goals, and as such may end up pleasing anti-environmental interest groups or anti-environmental electorates in order to win as many votes as possible. In sum, sceptics argue that individual rights, short-term electoral goals, lobbying and clientalistic relationships may hamper the positive effects of democracy on the environment.

To get a cursory intuition of the empirical relationship between environmental quality and democracy, I have displayed a visualisation of the *Environmental Performance Index* (EPI), a component index indented to measure overall environmental performance in a country, compared to each country's level of democracy measured with the Varieties of Democracy (V-Dem) Institute's *Polyarchy Index* intended to capture Dahl's (1971/1982) definition of democracy (Coppedge et al. 2021; Povitkina et al. 2021; Wendling et al. 2020). One notable trend here is that strong democracies are indeed associated with overall good environmental performance, but that there is more variation between democracies (e.g. defined as above 0.5 on the Polyarchy Index) than between autocracies:

Figure 2.1: Environmental Performance and Polyarchy, 2020 (EPI & V-Dem)



The EPI Index is measured on a scale of 0 to 100, where 100 signifies the highest attainable environmental performance. The Polyarchy Index (or EDI) ranges from 0 to 1, where 1 signifies the highest attainable level of democracy. The data is retrieved from the Povitkina et al. (2021) and Coppedge et al. (2021) data sets.

Democracy, democratization and forests. Returning to forests, previous literature may suggest that democracy's relationship with forests is more convoluted than for the environment in general. Didia (1997), making their own democracy index and using forest data, finds a robust correlation between higher levels of democracy Li and Reuvny (2006), using the Polity IV index of regime type find that democracy is monotonically associated with lower deforestation rates (Li and Reuvny 2006, p. 951). Others find that democracy on the micro-level yield environmental improvements. For example, a field experiment by Gatiso and Vollan (2016) in Ethiopia showed that democracy improved management of a community forest, and that groups cooperate more when the procedure is perceived as legitimate in a specific cultural context (Gatisio and Vollan 2016, p. 128).

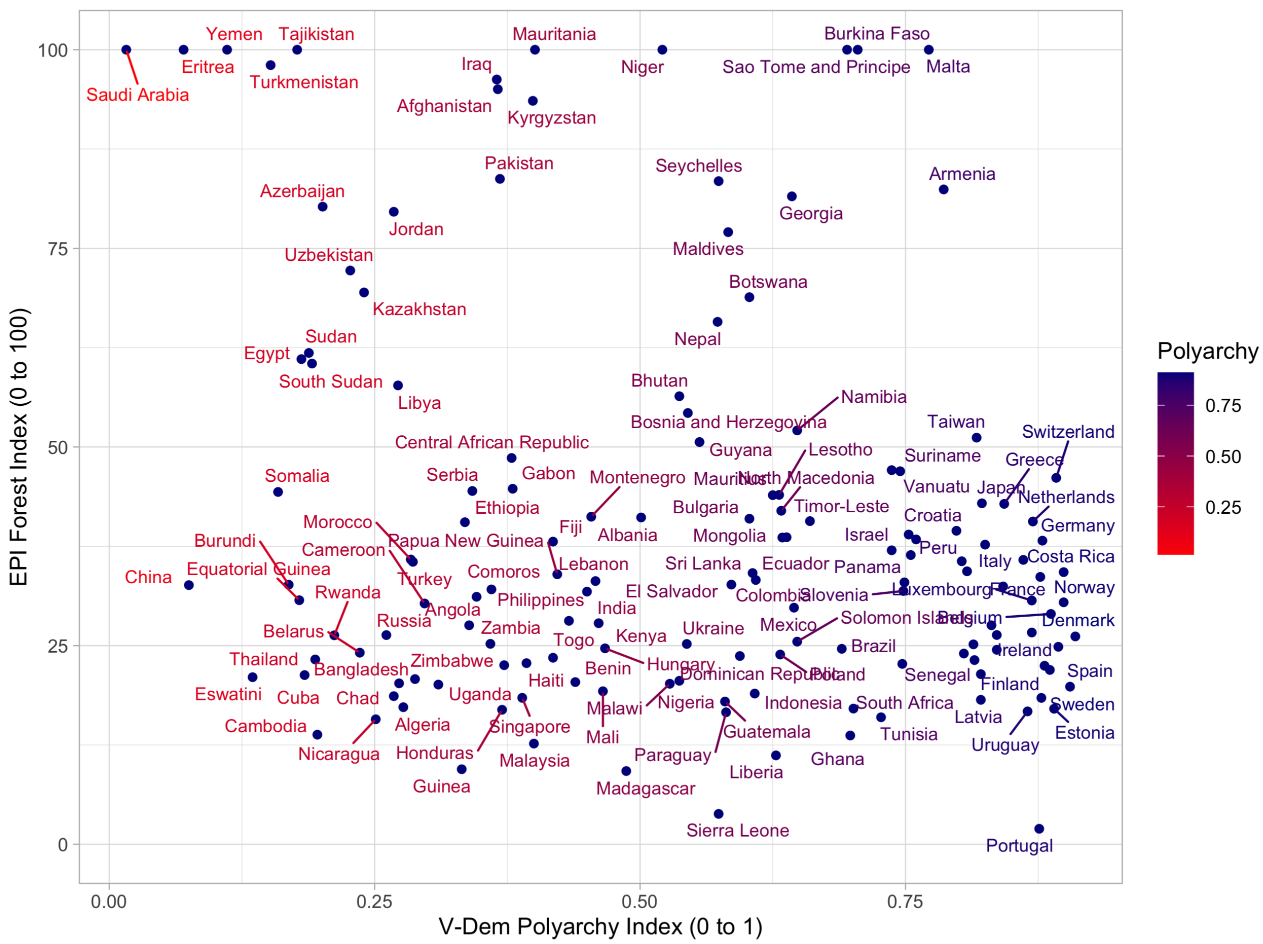
Others, like Buitzenzorg and Mol (2011), using the Polity IV and country-year data on forest change rates (1980-2000) from the United Nation's Food and Agricultural Organization (FAO), find that there is evidence of an inverted U-shaped relationship between deforestation-rates and democracy, and that countries in democratic transition (autocracies) experience the highest deforestation rates compared to autocracies and strong democracies, and that democracy has larger explanatory power of deforestation in their regressions than levels of income (Buitenzorg and Mol 2011, p. 59). Kuusela and Amacher (2016), also using the Polity IV index of regime type and country-year data find evidence for democratization (transitions) being associated with higher levels of forest loss during the first 5 years of the new democracy, a relationship they theorize to be a result of the new regimes rapidly expanding agricultural land that politicians use to stay popular and remain in power.

Similarly, several case studies examine the purposed link between electoral incentives and deforestation, as it is often considered the most plausible link between democracy and deforestation. Klopp (2012), using process tracing methods, argues that the destruction of several forest reserves in Kenya can be attributed to increased demand for political patronage in pre-election periods. Also in Kenya, Morjaria (2012) argues that the introduction of multiparty elections in 1991 led to targeted removal of protected forested land in areas pivotal for the election, using satellite data to show a clear distinction in forest cover loss between incumbent loyalist and opposition districts (Morjaria 2012, p. 23). At the local level there are various case studies finding a similar electoral link: Pailler (2018) finds that in Brazilian municipalities where mayors run for re-election deforestation rates are 8–10% higher than in non-election years. Burgess, Hansen and Olken et al. (2012) find "political logging cycles" in Indonesia, where deforestation rates increase during competitive elections.

As such, corroborating these observations as well as Albertus (2013) theory on distributive goods through land allocation, Sanford (2021) conducts an updated global study finding that transitions to democracy and competitive elections are associated with higher-than-average forest loss (Sanford 2021, p. 15). Sanford's study offers several advantages compared to previous studies, as it uses aggregated satellite measurements from the Song, Hansen, Stehman, et al. (2018) data set covering yearly data from 1982 to 2016 (instead of the FAO data, which covers forest change in 5-to-10 year intervals), as well as offers a global look at the competitiveness of national elections.

Turning to the EPI Forest Index this time for some guiding intuition, the relationship between democracy and forests may indeed be more complex. There seems to be more outliers (contingent on geography), and strong democracies do not appear to be associated with a similarly strong advantage vis-a-vis autocracies as for the environment in general (Coppedge et al. 2021; Povitkina et al. 2021):

Figure 2.2: Forest Index and Polyarchy, 2020 (EPI & V-Dem)



The EPI Forest Index scores forest management on a scale of 0 to 100, with a score of 100 indicating no tree cover loss. It measures tree cover loss as the average annual loss in forest area over the past five years, divided by the total extent of forest area in the year 2000. Forested areas include parcels with ≥30% canopy cover. Recognizing the greater value of mature forests, the index only looks at gross losses, not net. One obvious intervention is that the bivariate relationship does not take into account variation in countries' geographies. E.g. Saudi Arabia, an autocracy with a predominantly deserted geography, gets a perfect score (100/100) on the EPI forest index as it simply does not have forests to loose.

However, a limitation of the comparative literature on democracy and deforestation (and the environment in general) is that it tends to endogenize important characteristics of individual democratic regimes. Pertaining to the 'regime perspective' outlined in the *concepts* section, the make-up of incumbent regimes' political elites or key support groups may indeed affect environmental performance. In this regard, no studies have addressed the potential heterogeneous effect that incumbent' political support bases can have on environmental quality outside the case studies literature. For instance, Ferrante and Fearside (2019), in a salient example, show how business supporters and 'Ruralistas' (rural supporters) were key parts of Jair Bolsonaro's political support base when he was elected into office in 2019. Within other areas of the comparative politics sub-field, support coalition identity has been shown to alter a wide variety of outcomes: Albertus and Menaldo (2018) points out that levels of post-democratization economic inequality may be moderated by the identity and interests of former authoritarian elites. Wig, Dahlum, Knutsen and Rasmussen (2020) point to business-supported regimes being relatively influential in initiating interstate war. Gerring, Gjerløw and Knutsen (2022) also point to the possibility of the identity of certain support coalitions being more influential in affecting a country's ability to industrialize than others. However, there has been little attention given to how support bases of incumbent regimes may affect environmental outcomes *globally*. I argue that this research gap is of importance, as uncovering whether specific support bases of incumbent regimes are associated with higher levels of deforestation can allow scholars to better understand under which circumstances, and if at all, democracy is instrumentalized against the environment.

2.3 Summary

Above I have outlined some of the main purposed drivers of deforestation. Due to advances in remote sensing, there is now better and more accessible data on forest cover change than ever before, allowing scholars to separate between natural and anthropogenic drivers of deforestation. Nature itself creates grounds for disturbance event frequencies which creates natural heterogeneity in the forested landscape, resulting ecosystem renewal. However, the average occurrence rates of these disturbance events are changing due to anthropogenic climate change, and increases in disturbance events is strongly associated with increased deforestation. Economic incentive structures can promote deforestation for energy provision, agricultural production and extractive industries, with the latter two's growth capacity has been shown to be aided by trade openness, price elasticity and international demand.

However, the political dynamics that drive deforestation, as well as the role of political institutions is still not well understood. In the above literature review, I find evidence for democracy both mitigating forest loss and exacerbating forest loss, with electoral competition and patronage politics and clientalism being outlined as the key mechanisms driving forest loss. To further investigate this dynamic, I have suggested that attention to an incumbent regime's political support bases may yield insights into environmental outcomes such as forest change. Does the process of democratization and electoral competitiveness create the unfortunate situation of increased environmental degradation in the form of deforestation, hence contributing to large-scale collective action problems such as climate change, or is this effect moderated or exacerbated depending on the identity of supporters of the incumbent regime? As the empirical and philosophical debate regarding which political institutions is best suited to solve climate change continues (e.g. Mittiga 2022),[11] gaining generalizable empirical knowledge about the effect of these institutions is all the more important to make evidence-guided policy assessments.

[11] A recent article by Mittiga (2022) controversially suggested that authoritarian power may be legitimate in order to halt climate change.

Chapter 3

Theoretical Framework

> And into the forest I go, to lose my mind and find my soul.
>
> \- *John Muir*

If democratization is associated with higher levels of forest loss, it raises the question of under which circumstances democratization can come at the cost of the environment. As discussed in chapter 2, it is possible that the effect of democratization on forest cover change is heterogeneous across different contexts. To explore this relationship further I will build a theoretical proposition in this chapter. In social science, a theory can be considered a set of reasoned and precise speculations intended to provide an explanation of a social phenomena (King, Keohane and Verba 1994).

To create a theory, I first outline what relative value forests have for citizens/voters as well as incumbent regimes on a short- and long-term time horizon. This offers a better understanding of what political value forests have, a key to understanding the politics of forests. Secondly, I outline the purposed mechanisms of how deforestation can be linked to democracy by describing how politicians with a short time-horizons allocate forested land as patronage. Third, I synthesize the observations of Sandford (2021) with a theory on individual regimes' support coalition *identities* (Wig, Dahlum, Knutsen, et al. 2020), i.e., the identity of the key support groups needed by the incumbent regime to remain in power. My main argument is that different support coalitions may have different economic and political interests in society which in turn could affect rates of deforestation. Based on this argument, I outline a set of hypotheses using extant literature on the interests that rural and urban support groups may have in forested land. Lastly, I clarify the intentions of the hypotheses.

3.1 The Political Value of Forests

As pointed out in the introduction, about 90% of forests globally are located on publicly owned land (Malhi et al. 2008), making forest loss a political problem that can be affected by political institutions. Understanding the *relative* value that forests have for citizens as well as incumbent politicians can further our understanding of the political incentives to deforest. Below I outline how forests have both relative long-term and short-term value for the two groups:

Long-term value. Forests have inherent long-term value to citizens for a variety of reasons. First, forests can provide ecosystem services (Newell 2016) as they host pollinators that are essential to seed production and predators that control pest populations. Additionally, forests reduce *air pollution* (such as levels of particulate matter (PM)), decreasing respiratory and cardiac illnesses by acting as natural filters that purify water and help to recharge groundwater basins that are important for agriculture. Forests mitigate floods and droughts by preventing large fluctuations in the flow of rivers while preventing erosion and sediment loading that can make water more difficult to consume and shortens the lifespan of dams (Boelee 2011; Sanford 2021). Forests also attract tourists that bring domestic and foreign spending. Most of these benefits accrue to populations beyond those that are adjacent to the forest, and fall somewhere on the spectrum of positive externalities (sediment reduction) to pure public goods (CO_2-emissions reduction) (Chazdon 2008). As Sanford (2021) points out, these benefits accrue slowly by, for example, flood mitigation that would not be apparent except in high-runoff events, and the effects of air quality on health can be latent for tens of years. Still, there is growing evidence that negative environmental affect on citizens' livelihoods, which in turn can reduce support for an incumbent politician (Obradovich 2017). Lastly, forests can also have inherent value by themselves (i.e., the 'deep ecology' movement, see Næss 1984), or for cultural reasons. As a result, forests can indeed provide long-term public goods that can help rally support for political incumbents.

Short-term value. On the contrary, forests also hold inherent short-term material value in the form of an exhaustible common-pool resource.[1] A conservative estimate suggests that the pure material value of forests as timber is somewhere around $ 150 trillion USD (BCG 2020). As such, logging companies can benefit from decreased protections of forests (Pailler 2016; Burgess et al. 2011). However, more commonly (or in conjunction with logging) deforested land is subsequently used for agricultural purposes as the soil is high in nutrients such as nitrogen and phosphorous, or used for extractive industries if close to a source of a valuable mineral or hydrocarbons (Rudel 2013; Sonter, Herrera, Barret et al. 2017). In this regard, the value of forests are different according

[1] Ostrom (2005) defines a common-pool resource as a resource that shares the subtractability of a private good while having the difficulty of exclusion of a "pure" public goods (Ostrom 2005, p. 25)

to Sandord (2021). Rather than providing value over time in the form of public goods, the value associated with cutting down forests is comparatively immediate, and directly attributable to the politicians that provided it (Sanford 2021, p. 5). Moreover, the value of the forest accrues directly to the company or people who are able to use the forested land. Consequently, forests can also provide short-term benefits for the key constituencies of incumbent politicians. In the next section I will explore this mechanism in detail.

Summary: The Value of Forests		
Duration	Value for Citizens/Voters	Value for Incumbents
Short-term	Timber, energy provision, heating, land for agricultural use, development of commercial land, development of extractive (minerals or hydrocarbons) industries.	Political support, campaign donations or increased taxation.
Long-term	Air quality improvements (and reduced respiratory and cardiac diseases), ecosystem services (pollination, pest control etc.), CO_2-reduction, flood and drought mitigation, preservation of cultural heritage, tourism.	Political support.

3.2 Mechanisms: Clientalism, Land Use and Forests

Sceptics of democracy's effect on the environment note that the relatively short time-horizon of politicians in democracies may hamper effective long-term projects such as managing forests. One of the key purposed mechanism that contributes to this dynamic is clientalism, the political practice where incumbent 'patrons' provide favors in exchange for political support from 'clients' (Berenschot 2018, p. 1564). Keefer (2007) points out that young democracies (countries that have recently experienced a democratic transition) tend to experience more clientalism than more established democracies, as politicians cannot credibly commit to promises, incentivizing them to prefer clientalistic politics: under-providing non-targeted public goods, and engage in *rent-seeking* activities while over-providing target goods to key supporters (Keefer 2007, p. 804).[2] Albertus (2013) calls these targeted goods *distributive good*, goods that can be distributed to buy political support. Patrons use distributive goods in many different forms, whether they are one-time such as handouts of cash, food, building materials or other consumables enjoyed by the client. It could also be more permanent, or long-term benefits, such as selective allocation of land and infrastructure/welfare provision (electricity, water, communications provision, access to education etc.). As such, distributive goods are clearly distinguishable

[2] Rent-seeking refers to the process of seeking to gain larger profits by manipulating public policy or economic conditions, especially by means of securing beneficial subsidies or tariffs, making a product artificially scarce or other tactics (OED 2022).

from public goods, which are meant to benefit nearly all the citizens of a given society (for a definition, see chapter 2.1).

As land use is of particular importance in many developing states, Albertus argues that land can be a particularly effective distributive good. Land has three distinct aspects that separates it from other distributive goods: (1) Allocated of land provides rewards to the recipients in the future without having to receive additional payments. The client can produce on the plot of land in future periods, receiving a relatively constant stream of payments. (2) The value of the land can also be significantly increased by providing credits and technical assistance, leaving the patron with additional future leverage over the client. Lastly, (3) distributed land is often very difficult to take back and redistribute again, making its supply limited (Albertus 2013, p. 1086). As such, allocating land is a potential one-off, medium-risk, and high-reward proposition that politicians can use to aggregate political support.

As touched upon in chapter 2, Sanford (2021) points at that forests, and the land its on, do indeed mirror many of these characteristics. However, allocation of forested land depends on land use rights. These rights vary in formality - either being transparent and formal, or hidden and informal. Formally they come in the shape of property rights or permits allowing companies or people to legally exploit the forest for their own gain in the form of logging, agriculture or mining (Sanford 2021, p. 4).[3] Alternatively, I argue that incumbent politicians may also informally *encourage* deforestation by temporarily reducing the formal or informal protection of forested land (for example, by reducing monitoring of the forests for certain periods in time). Whether formal or informal, forested land can be allocated by incumbent politicians to target the key constituencies they depend on for support, allowing local firms or certain citizens to deforest for their own self interest. This could in turn create jobs or economic growth to particular area, which may also result in direct revenues for the politicians in the form of taxation or political donations.

Crucial to Sanford's (2021) theoretical contribution is that the short-term political value of distributing forested land is particularly high during times of democratization, when new politically enfranchised part of the population enter a country's *selectorate* (see definition in section 3.3, Bueno de Mesquita, Smith, Siverson, et al. 2003), and thus the political value of removing forest protections increases for the incumbent regime. As such, I suggest that using data capturing the identity of the incumbent regime's support bases or key elites may allow scholars to further shed light on the potential heterogeneous treatment effects of different political interests on forest loss. Below I elaborate on this theoretical proposition, its origins, and its benefits for the study of deforestation and environmental

[3] Some countries regulate forest use by instituting requirements for forestry, criteria for how many trees that can be logged within a specific time period.

degradation.

3.3 Theory: Supporter Identity and Deforestation

Whether studying politics or discussing it colloquially, scholars often evoke the concept of individual politician's 'support base', referring to the people the politician relies on to stay in power. A much debated proxy for capturing the characteristics of a polity's political support base, participants or elites is presented in *selectorate theory*, as purposed by Bueno de Mesquita, Smith, Siverson, et al. (2003). Briefly explained, the theory poses a parsimonious relationship between a polity's ability to provide public goods (such as environmental quality) as a function of the size of a polity's *selectorate* and *winning coalition*. The selectorate is defined as the part of the population who meets a polity's criteria for political enfranchisement, while the winning coalition is defined as a subset of the selectorate with sufficient size to endow the leadership with political power over the remainder of the selectorate. In exchange for their support, the members of the winning coalition receive private goods from the incumbent (Bueno de Mesquita et al. 2003, p. 41-51). One of the key observations of Bueno de Mesquita et al. is that for politicians to reach their personal political ambitions, they must retain political survival. Therefore, savvy politicians in both democracies and autocracies must consider how their decisions impose costs or benefits to the winning coalition that endow them with power, as this affects their ability to remain in office.[4]

Due to their institutional nature, democracies tend to have large winning coalitions as universal suffrage promotes the election of a more diverse groups of representatives, while autocracies tend to have small winning coalitions, pertaining to the polity's elite, or the clandestine inner circle of a dictator's cabinet.[5] These differences in size in turn influence leaders' decision-making, as he/she attempts to cast an optimal balance of between providing enough private goods to the winning coalition, and public goods to the overall population. The larger the selectorate and winning coalition, the more likely leaders are to allocate funds and effort into delivering public goods to the entire population. As such, the theory suggests that democracies should be more inclined to deliver environmental public goods such as forest protection.

However, a key missing element in Bueno de Mesquita et al.'s original theory is that

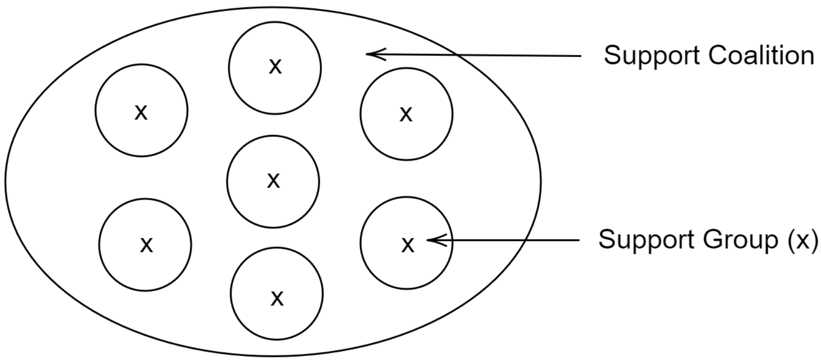
[4] While Morgenthau (1967) argued that politicians' desire for power was rooted in human nature (animus dominandi), there may be several rational choice-based reasons for why politicians want to remain in power. For example, Wintrobe (1998) suggests that power brings both prestige and status, as well as a prerogative to rule over other people. Moreover, politicians may also want to stay in power to maximize personal consumption or want to realize an ideological agenda that they see themselves best equipped to implement (Gerring, Gjerløw and Knutsen 2022, p. 105791).

[5] Importantly, in weak democracies, the selectorate may have effectively been reduced by restricted voting-rights or economic constraints, giving some groups a disproportionate ability to alter policy.

that the variation in interests within the winning coalition (beyond wanting more private goods) is not covered by the model (p. 75). The original theory addresses the size of the coalition, but not the *identities* of the coalition. Indeed, the selectorate and the winning coalition are modelled as homogeneous groups, with its composition bearing no effect on the incumbent's policy decisions. As Gallagher and Hanson (2015) point out, the assumption of homogeneity results in an unrealistic tie between public good provision and political rights as the qualitative differences in the membership of winning coalitions are just as important as differences in size (Gallagher and Hanson 2015, p. 374). Indeed, the identities of members of the winning coalition may reflect different political and economic interests in a society, which gives the availability of distributive goods a relative value dependent upon their identity.

As described in section 2.1, the concept of the *support coalition* attempts to encapsulate this dynamic (see figure 3.1). As each coalition consists of different support groups, these can impose costs and benefits to the incumbent regime, or so-called *constraints* depending on their preferences. Weeks (2012) defines domestic constraints as the limitations and consequences that domestic audiences and intuitions have on a leader's wish/decision to make a decision. There are two types of constraints, *ex ante* constraints which hinder a leader from making a decision in the first place and *ex post* constraints that hold the leader accountable for making the decision (Weeks, 2012, p. 328).

Figure 3.1: Conceptual View of the Support Coalition and its Support Groups



An interesting aspect is the potential outcomes that can be associated with support coalitions' identity surrounding democratic transitions, as the support coalitions of most non-democracies tend to be small (ex-ante democratization), and the expansion of both the selectorate as well as the support coalitions ex-post democratization often introduces new groups to the coalition, which alters the identity make-up of a polity's support coalition. This change may reflect those new enfranchised parts of the population gets a say in political and economic decision-making within a regime's institutions. Similarly, incumbent regimes/politicians must reassure supporters of the benefits of keeping the incumbent during times of elections as they need to their support groups to be re-endowed with political power.

As explained, Sanford's (2021) observes that the relative political value of forests is altered during times of democratization, as the circumstances increase their relative value for politicians as a distributive good following increased competition for political survival. I argue that this effect of democracy is moderated by the identities of the support needed by the incumbent to retain office. The value of forests for some support coalitions may be greater than others, as some supporters may value the forests for their short-term material value (by logging), some for their long-term positive externalities as a public good (such as improving air quality or reducing CO_2-emissions), or some for psychological factors such as being tied to individuals' level of environmental concern (Unsworth and Fielding 2014). The value of forests may also be temporal in nature, varying according to political opinion, economic needs and opportunities. Given the expanding size of the support coalition following democratization, politicians may have to factor in a more varied set of interests than under the old autocracy. Yet, at the same time autocratic leaders also depend on support from key support groups in the population to stay in power and are often in a more volatile position than their democratic peers as the consequences of losing power may be higher. If so, then they may be equally (if not more) willing to distribute goods such as forests to remain in power. As such, I argue that it is also possible that changes in the support coalition (for example, the introduction of a new group) have an independent effect on forest cover change, regardless of regime type.

Below I have made two graphical illustrations based on these expectations. First, the scenario where democracies amplify the willingness of incumbent politicians use distributive goods, the identity of support coalition's moderates the effect of democracy on forest loss (see figure 3.2). Second, considering that the willingness of politicians to use distributive goods is equal for democracies and autocracies, the identity of the support coalition has a direct effect on forest loss (see figure 3.3).

Figure 3.2: Purposed Causal Diagram: Moderation

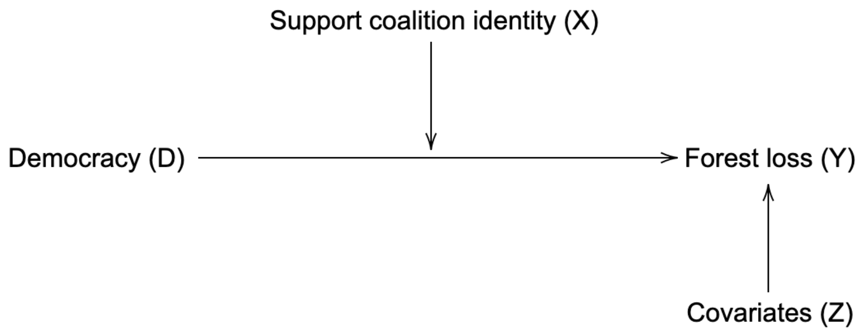
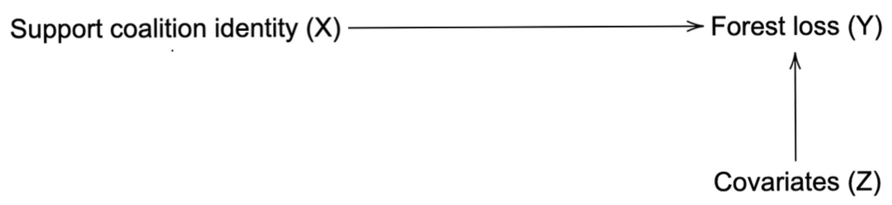


Figure 3.3: Purposed Causal Diagram: Direct



In the next section I explore some of the possible incentives that politicians in different support coalitions have to utilize forests, and I divide them into in two main groups, one group with a distinctly "rural" identity, and one group with a distinctly "urban" identity, with some sub-groups hypothesized to being even more adverse (or beneficial) to forests.

3.4 Specifying Hypotheses

In this section I specify my hypotheses. Based on the above, I outline my main hypothesis. This hypothesis pertains to the idea that the identity of support groups moderate the purposed deforesting effect of democracy (found by Sanford 2021):

> **H1:** *The effect of democracy on forest cover change is moderated by the identity of the regimes' support coalition.*

Having outlined my main hypothesis, I include a second hypothesis with the motivation to probe for the *total effect* of support coalition identity on forest cover change. In this regard, total effect refers to the effect that different coalitions have when I factor out regime type, assuming the effects are homogeneous across democracies and autocracies:

> **H2:** *Support coalition identity has a non-zero effect on forest cover change.*

I move on to synthesize a set of exploratory sub-hypothesis for my main hypothesis based on an informed speculation about the particular incentives that different support groups have to deforest. As mentioned, I divide the support groups into two main categories: Rural supporters and urban supporters.

3.4.1 The Incentives of Rural Supporters

Consider democratization in a country where large parts of the rural population and elites may have gained political enfranchisement. I define rural groups as citizens reflecting different rural interests, such as for example the peasantry (working class), family farmers (middle class), or members of a rural community.[6] For these groups the potential value of deforestation can be considered relatively high as they can sell forests as a commodity through logging, use it for energy production, or clear the forest for agricultural purposes. Consequently, politicians wanting to stay in power need to take into consideration these new needs. Harding (2019, 2021), for example, finds that in 27 African countries, democratization and competitive elections have induced governments to adjust policy to serve rural needs to compete for primarily rural votes following democratization. Indeed, the introduction of these groups to the support coalition may have created a "rural bias" in policy-making at the relative detriment of urban groups (Harding 2019, p. 252). Given such a proposition, democratization under rural groups may have adverse consequences for forest management if there groups have a relatively high short-term value of utilizing forests. As such we could expect the marginal effect of democracy on forest cover change to increase. I have previously mentioned the salient example of Kenya (Klepp 2013), where after country's first competitive election in 1993, the entrance of rural groups in

[6] In this thesis I define social class broadly: A group of people within a society who possess similar socioeconomic status or characteristics.

Kenya's support coalition may have led incumbent politicians to encourage and allow for deforestation in other to gain political support.

Conversely, there is also the possibility rural groups may also have an inherent interest in managing their nearby forests as they rely on them for sustained production have and/or have an inherent cultural interest in their conservation, and their introduction into the support coalition may yield more information and a better understanding of what is happening in rural areas for policy makers. Introduction of rural groups into Mexico's support coalition following its transition to democracy in 2000, may have encouraged better rural preservation efforts of forested areas (Klooster and Masera 2000, p. 259). Other examples, albeit not from a democracy, such as the rural Imazighen communities in Morocco made their own ad hoc forest conservation and production practices that interlinked with the social, political and spiritual dimensions of their community, which ultimately led to more sustainable forest management in areas in northern Morocco (Genin and Simenel 2011, p. 257). There may indeed be good reasons for rural groups managing forests adequately, and their introduction to the support coalition bettering the purposed deforesting effect of democracy. Or, as seen in the Morocco example, that these groups have an independent effect on forest cover change regardless of regime type. Therefore, my first set of hypotheses are the following:

> H1a: *The marginal effect of democracy on forest loss decreases when rural supporters are in the support coalition.*
>
> H2a: *Rural supporters have a non-zero effect on forest cover change.*

Certain rural supporters may have been more detrimental to forests than others. Agrarian elites and/or large landholding farmers is one group that historically has had an out-sized effect on forest loss through ownership of agricultural industries and large plots of land. For example, evidence from the 'third wave' of democratization in Latin-America in the late 20^{th} century as well as the first decade of the 21^{st} century suggests that agrarian elite have had a large impact on the regions economic development, and their presence in politics has been shown to alter post-democratization outcomes, such as levels of overall inequality and inequality in land-ownership (Albertus 2017; Albertus and Menaldo 2018). According to Milamanda (2019), this has given the agrarian elites in the region a profitable advantage during the commodities boom of the 2000s, in which these elites turned to political base-building to keep their land from being expropriated. In Chile and El Salvador, for example, these elites have invested heavily in supporting and building conservative parties representing their interests (Milmanda 2019). Angeles (2009) finds similar patterns in Southeast-Asia; a case study of the Philippines also shows that agrarian elites in Northern Mindanao have protected their economic privileges and survived the political challenge (land expropriation) posed by migrant politicians through rent-seeking activities (Angeles 2009, p. 688). It is possible that in a democratizing country where agrarian elites have a dominant role in the support coalition, the marginal effect of democracy on forest loss *increases* as these elites now may have a profit-seeking interest in over-utilizing their land due to the favorable economic environment that democracy creates (Acemoglu, Naidu, Restrepo, et al. 2019, p. 48). Indeed, as Albertus (2017) points out, democratization gives agrarian elites robust legal property rights, as well as long-term stability that they did not enjoy under the old autocracy (Albertus 2017, p. 272), all of which could encourage further land-utilization. Perturbingly, although less likely, it is possible that the monopoly of land that agrarian elites have had historically can also have resulted in the under-utilization of land, coming at a high cost for human development and prosperity, but may have resulted in less use of forests. In light of this, it is possible these groups themselves have more explanatory power on forest change than regime type, hence having an independent effect. My second set of hypotheses follow a similar pattern as the previous ones:

> H1b: *The marginal effect of democracy on forest loss increases when agrarian elites supporters dominate the support coalition.*
>
> H2b: *Agrarian elites have a non-zero effect on forest cover change.*

3.4.2 The Incentives of Urban Supporters

The relative value of forests for urban supporters may be distinctly different. I define these groups as urban factory/industrial workers, labour unions, as well as middle-class workers such as non-industrial workers in the service sector and owners of small- and medium-sized businesses. These urban supporters may enjoy the passive public goods that forests provide (reduction of air pollution, drought mitigation, ecosystem services etc.), but not appreciate the immediate material value of forests. Urban supporters may also care more about overall environmental quality as a function of cities often being wealthier and having higher incomes than rural areas, as there is no immediate need to utilize the nearby environment (Bloom, Canning and Fink 2008, p. 772). As such, transition to a urban-enfranchised democracy may yield more beneficial forest management, causing less forest loss or reforestation. Yet, at the same time it is also possible that these groups have an independent effect on forest change, regardless of regime type. For example, Liu and Mu (2016), using survey data from China, finds that higher-income urban residents in the eastern provinces of China tend to be more concerned about the environment than rural residents (even high-income rural residents), although the effect is moderated by years of education (Liu and Mu 2016, p. 125). In sum, is therefore possible that urban groups care more about the long-term public goods that forests provide than rural groups due to socioeconomic reasons and awareness about forests long-term benefits.

However, the benefits of urban supporters may not be as clear cut. Growing cities may demand more land, food or other commodities as cities expand, all of which is land intensive and correlated with deforestation. Additionally, it could be that urban groups have a sense of relative 'detachment' from the nature vis-á-vis rural groups, make them care less, or be less aware of their possible adverse impact their behaviour has on forests. DeFries, Rudel, Uriate, et al. (2010) using satellite data from the years 2000 to 2005 finds that, in line with this intuition, that urbanization and growing migration to cities were associated with higher levels of tropical forest loss. They argue that as people migrate to cities, their consumption preferences change alongside increased income, promoting land use and deforestation in the form of industrial-scale, export-oriented agricultural production. They also argue that there is a synergy between rural areas depopulating, and urban areas increasing consumption, as urban demand now drives unsustainable deforestation in the depopulating areas (DeFries, Rudel, Uriate, et al. 2010, p. 178). If so, politicians in urban supported regimes may have an inherent self-interest in supporting incumbent regimes that directly or indirectly promote deforestation. Given the stronger economic growth of young democracies, in addition to more export-oriented commerce than under the old autocracy, I argue that urban supporters will push the incumbent regime to favor development that is land-intensive, hence having an effect on deforestation. Given this, my third set of hypotheses is the following:

> H1c: *The marginal effect of democracy on forest loss increases when urban supporters are in the support coalition.*
>
> H2c: *Urban supporters have a non-zero effect on forest cover change.*

Next, one particular support group identity that is brought up in the case study literature on forest loss are business elites. I define these groups as wealthy entrepreneurs, shareholders or company owners. Standard microeconomic theory would suggest that these urban business elites, if included in a regime's support coalition, may engage in rent-seeking motives to maximise profits (Varian 1992, p. 25). As a result, this group may cast an out-sized effect on the environment compared to other urban groups (or rural groups for that matter), particularly considering that these elites may own extractive industries in forested areas and may see personal profits upon supporting deforestation activities (for mining and deforestation see Sonter, Herrera, Barrett, et al. 2017). As discussed in chapter 2, business elites may be particularly efficient at altering policy by employing special interest groups or clientalist networks (e.g., Brulle 2018; Grossman and Helpman 2001; Vesa et al. 2020). For instance, when Brazil's government tightened the forestry policy during the early-2000s to limit over-exploitation of the Amazon, it led to a reaction by Brazilian business elites. Instead of directly confronting the executive branch in Brazil by trying to win court cases in the judiciary, these groups directly lobbied lawmakers in the Brazilian legislative to change the law, partially resulting in the Brazilian House of Representatives making major exceptions the new Forest Code of 2011, which increased forest loss in the subsequent years (Sant'Anna and Costa 2021, p. 4; Castelo 2015; Horochovski et al. 2016).[7] Fukuoka (2012) points to a similar dynamic in Indonesia, where after the beginning of *reformasi* (reform and democratization) in Indonesia, business entrepreneurs have increasingly turned to national politics, securing seats in Indonesia's parliament and fostering clientelistic networks to the executive, effectively growing the number of business elites within the support coalition. Cisneros, Kis-Katos, Nuryartono, et al. (2021) point out that Indonesian business elites are particularly savvy in lobbying support for favorable land change policies during competitive election. In sum, when business elites dominate the incumbent regimes' support coalition in a democracy, this may increase the marginal effect of democracy on forest loss.

Yet at the same time, business elites may also encourage more efficient management of natural resources (Berge 1994), such as forests. The same microeconomic theoretical arguments suggesting that these elites may have an adverse effect on forest, may also suggest that these elites may be concerned about the adverse effects of their economic initiatives have on forests, as it could have an impact on their mid- to long-term profits. Payne (1996), for example, suggests that business interests are increasingly taking into account the environmental costs ("externalities") of their economic activities: "[C]apitalism is not the cause of environmental degradation. After all, non-market economies have exploited the environment quite ruthlessly, and mounting evidence indicates that some businesses in open economies are finding strong incentives to protect the environment" (Payne 1996, p. 41-55). Indeed, both shareholders and boards of large corporations increasingly emphasize the need to balance profit-making with holistic priorities in society, and as such an increasing number of companies adopt corporate social responsibility practices. In turn, these practices can allow business elites to achieve competitive advantages in a economy moving towards sustainability, as well as demonstrate their commitments to be socially responsible (Zhang, Oo and Lim 2019, p. 563). However, given the evidence in the previous, I deem this less likely. I structure my last set of hypotheses similarly as for the previous groups, with one hypothesis targeting the marginal effect of democracy, and another hypothesis probing for the possible independent effect that these groups have on forest change, regardless of regime type:

H1d: *The marginal effect of democracy on forest loss increases when urban business elites are in the support coalition.*

H2d: *Urban business elites have a non-zero effect on forest cover change.*

[7] Sant'Anna and Costa (2021) conducts a cost-benefit analysis of the 2011 Forest Code by quantifying the economic cost of the deforested CO_2-emissions, finding that the "[...] cost could be as large as 16 times higher than private benefits from cattle ranching activity" (Sant'Anna and Costa 2021, p. 11).

To give some intuition of the theoretical expectations outlined above, I have visualized them below in figure 3.4. In this graph d represents a binary intervention starting at time t, i.e. a transition to democracy or the entrance of a support group into the support coalition (or an interaction between the two) and $t + x$ reflects the expected change in forest change. I expect a time lag of the effect, as forest change (loss or re-growth) takes time to aggregate following an intervention.

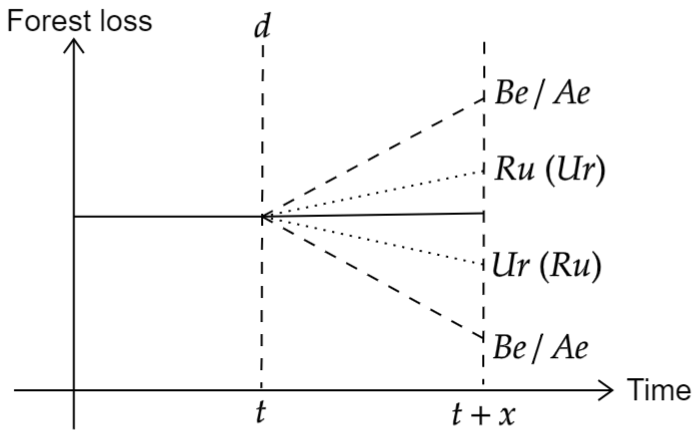


Figure 3.4: Visualization of Theoretical Expectations

Be/Ae refers to business- and agrarian elites. Ru/Ur refers to rural- and urban supporters.

As seen above, I have slightly different expectations for the different groups. I expect that urban and rural groups (Ur and Ru), may not have as a detrimental effect on forest cover change as for when the elites dominate the support coalition (Ae and Be) given that these groups may have a more salient impact on decision-making.

3.5 Clarifications

Before moving on to the chapter covering my use of data, subsequent operationalization of variables and use of methods, I want to clarify some aspects of the above hypotheses. First, the purpose of this thesis is not to establish a causal relationship between the presence of certain supporters and forest loss, but rather investigate if there are statistically significant associations that highlights the different effects of democracy, which may validate further enquiry into the dynamics of political support bases and their influence on forests. Second, I want to emphasize that both rural and urban groups may have real and legitimate needs for land use and deforestation, whether it be for the provision of energy, food or shelter. Indeed, the world needs more efficient farmland, particularly in sub-Saharan Africa where both low levels of labor productivity as well land productivity create food supply problems, making the region more dependent on international trade (Jayne and Sanchez 2021, p. 1045).

Chapter 4

Data and Research Design

In this chapter, I present the data that will be used to explore the hypothesized theoretical relationship presented in chapter 3, as well as discussing how the reliability and measurement validity concerns of satellite data as well as expert surveys. These data sets have been merged, cleaned and prepared for analysis using the 'countrycodes' and 'dplyr' packages in R (Arel-Bundock et al. 2018, Wickham et al. 2018). After presenting the data, I will proceed to operationalize my independent variables, my purposed moderation variables as well as the dependent variables. Lastly, I outline the statistical methods I will employ to test the outlined hypotheses, covering both the model for the main analysis - ordinary least squares with two-way fixed effects, and the model used for the robustness tests - Mahalanobis distance matching with panel data. Additional summary statistics can be found in appendix B.

4.1 Forest Cover Data: 1982-2016

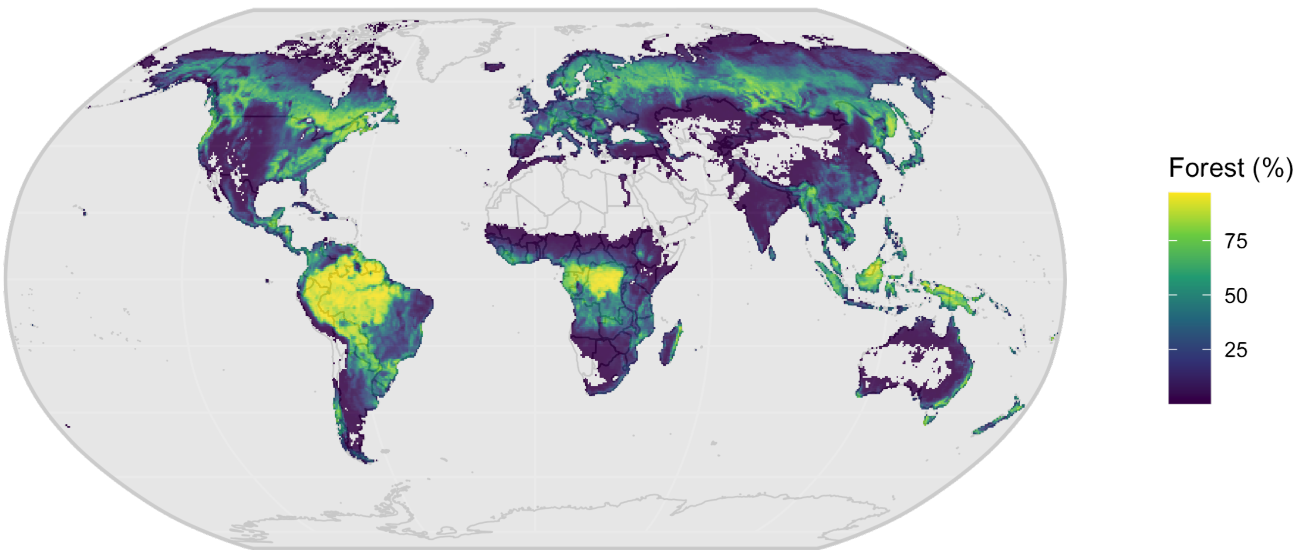
The original data on forest cover are 0.05° grid cells originally sourced from the Song, Hansen, Stehman et al. (2018) data set. This type of data is aggregated from satellite measurements undertaken by the NASA/USGS's Landsat program, and converted into squares of 5.5 x 5.5km, measuring percentage and type of forest in each square. This type of cell are formally referred to *C-squares* (concise spatial query and representation system) which is an international standard for representing geographically coded data in squares maintained by the World Meteorological Organization.[1] Forest is operationalized as the presence of vegetation with a canopy over 5 meters tall within the square,[2] and is measured using the satellites' advanced very high resolution radiometer (AVHRR) instrument to measure vegetation cover over the globe on an annual basis. The original data set provides temporal coverage from 1982 to 2016, and differentiates between the type of forest that has been measured (i.e. tropical forest, boreal forest etc.). The data set

[1] I will refer to these as grid cells for the remainder of this thesis.
[2] In biology, the canopy is the above ground portion of a plant cropping or crop, formed by the collection of individual plant crowns.

that I use is the one by Sandford (2021), which modifies the original Song et al. (2018) data by merging the grid cell data with data on national, provincial and local administrative boundaries from GADM (2022) and various socio-economic indicators from the world development indicators data set by the World Bank (WB 2017), while excluding all observations that never have forest cover from 1982 to 2016 as they cannot lose forest. This results in a data set with a total of 158,423,948 forested cell-years (Sanford 2021, p. 6-7).

For this thesis, I use an up-scaled version of the Sanford data set with a resolution of 0.5°, making grid cells of 55 x 55 km at the Equator (100x larger cells). I also use country-level-aggregated data for robustness checks. This results in a total of 1,787,050 cell-years and 5,735 country-years. The main reason for why I do not use the full extent of the data is due to the lack of computing power, as the original data set requires high-performance computing (HPC, a supercomputer) to be replicated.[3,4] The spatial distribution of the up-scaled 0.5° forested grid cells are displayed below for 1982 and 2012, showing 30 years of global change in forest cover:

Figure 4.1: Forest Cover, 1982

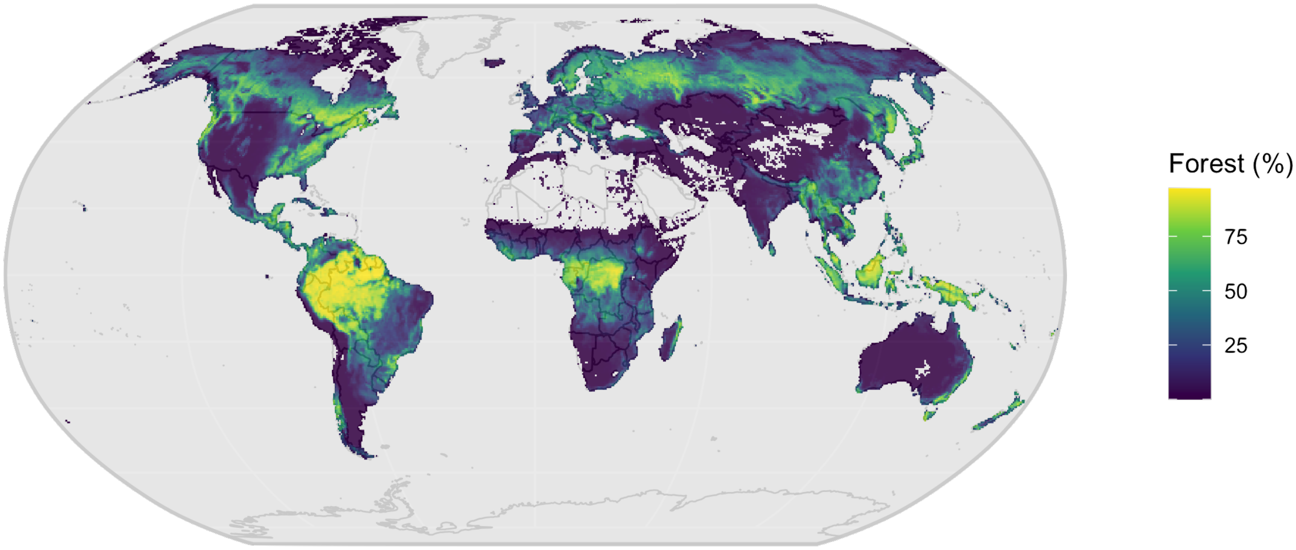


Robinson projection of global forest cover in 1982 using 0.5° grid cells generated in R.
Note that the cells are distorted according to the projection. Data: Song, Hansen, Stehman, et al. (2018).

[3] In the replication data, Sanford (2021) notes that he uses a Quad Xeon E7-4870v2 with 120 threads and 1TB of RAM, using a total running time of 18-24 hours for all data cleaning, merging, and analyses.

[4] While this could technically be fixed by renting time on a university-wide clustered HPC, that would be beyond the financial scope of this thesis. However, replicating the results of this thesis using the full 0.05° resolution data set can be done by running my R scripts using HPC as the variables are similar across different levels of aggregation.

Figure 4.2: Forest Cover, 2012



Descriptive patterns. Looking at the projected data, one notable trend here is that contrary to the popular belief that total forest area has declined globally, total forest cover has actually increased by 2.24 million km^2 from 1982 to 2016 (+7.1% relative to the 1982 level). This overall net gain is the result of a net loss in the tropics (particularly across the Congo, Amazon and Indonesian rain-forests) being outweighed by a net gain temperate continental forest and boreal coniferous forest in Europe in Asia (+726,000 km^2 and +463,000 km^2), as well as tropical shrubland in Australia and the Sahel region (among others, +417,000 km^2). While these gains provide observational evidence for growing carbon sinks in non-tropical regions, the biomass of these types of forests are considered lighter than tropical forests. Additionally, due to the larger biomass of tropical forests, these forests contribute significantly to global cooling (Lawrense, Coe, Walker, et al. 2022), but also release more CO_2 into the atmosphere when deforested (Song, Hansen, Stehman, et al. 2018, p. 642).

Reliability and internal validity. Briefly explained, reliability refers to the overall consistency of measurement, meaning that the test produces similar results under consistent conditions. Unreliable results are caused by unsystematic and random errors, related to the procedures of collection, coding and treatment of the data (Hellevik, 2002, p. 152). Internal validity will in this section be discussed in terms of measurement validity, where the observations meaningfully capture the ideas in the outlined concepts (Adcock and Collier 2001, p. 529)

The satellite data itself has several unique attributes. First, the data provides global and continuous coverage of an environmental indicator, covering 34 years of forest change in total, making it the one of the environmental indicators that provides the most detailed and comprehensive coverage. Other estimates of environmental indicators such as green house gas emissions (GHGs) or air pollution also provide relatively high-accuracy, but not the same level of spatial detail and coverage. Secondly, the method of measurement has very high reliability, given the accuracy of the AVHRR equipment. While the data differentiates between different types of forest, a real caveat in terms of measurement validity is decision by Song et al. (2018) to measure forest cover as vegetation of 5m canopy height, something that been shown to partially conflate the difference between natural forests and trees that are grown as crops. This results in the data set underestimating the total extent of global forest loss and makes it less suitable to study loss of biodiversity (Tropek et al. 2014, p. 981). However, while the 5m cut-off may to some extent be arbitrary, it is also considered a limitation of the technology, as 5m is the height at which satellites can reliably detect forest (Forestwatch 2016). Lastly, a major strength of satellite data in terms of reliability is that it is not prone to interference by parties that seek to misrepresent or conceal information such as, for example, state-actors attempting to downplay the extent of environmental degradation or emissions by modifying official statistics. This makes the data suitable to for exploring environmental relationships in countries with lower levels of democracy (for example, lacking freedom of information or lacking government accountability), or countries with lower quality of governance (for example, high levels of corruption). Consequently, the data provides both high degree of reliability and relatively high degree of measurement validity.

4.1.1 Dependent variable: Forest Cover Change

I use two different types of dependent variable, offering comparison across different levels of geographic aggregation: One dependent variable on the grid cell level, and one the country-level. These two variables share the characteristic of reflecting the year-on-year difference in forest cover. Kernel density estimation plots supplied in appendix C indicate that the dependent variable is normally distributed with heavy tails for both the cell-level and country-level dependent variable.[5]

0.5° grid cell forest change (%, t-1 to t+0). For my first dependent variable is called "forest.diff" in the data set, used for the main analysis. As mentioned, this variable is the up-scaled version of Sanford's (2021) data, uniting the smaller grid cells into larger 0.5° grid cells covering 55 x 55km making up a total of 1,787,050 cell-years (both grid cell measurements are at the Equator, and the size differs somewhat with the curvature of the Earth). This variable reflects the percentage point change in forested land-cover of each cell-year from the previous year. The dependent variable exhibits a unit root in levels, which suggests that taking a first difference produces more consistent results than including a lagged dependent variable. A value of -1 means a 1 percentage point loss of forest

[5] I discuss the implications of heavy tails in appendix C.

within a cell, and a value of 1 means a 1 percentage point gain of forest within a cell. One of the key advantages of using the grid cell data is that it distinguishes between different types of forest. I therefore include a second version of this dependent variable with a restricted sample only targeting *tropical forests*, making up a total of 595,585 cell-years between 1982 and 2016.[6] The reason for why I include this variable is the particularly important role that tropical forests have in mitigating climate change, as well as their amplified potential to release CO_2 when deforested.

Country-level forest forest change (%, t-1 to t+0). My second dependent variable is called also called "forest.diff" in the data set, and for the robustness test in chapter 5.3. This variable is also made up by a further up-scaled version of original Sanford data set, in which the grid cells of a country are combined to represent the average change among forested cells in a country in a year. In practice, this means that percentage point forest change is weighted equally for a large country like Brazil and a small country like Denmark. Similarly to the cell-level dependent variable, this variable reflects the percent change in forested land-cover of each cell-year from the previous year. Hence, a value of -1 means a 1 percentage point loss of forest within a country. The country-aggregated data makes up a total of 5,735 country-years.

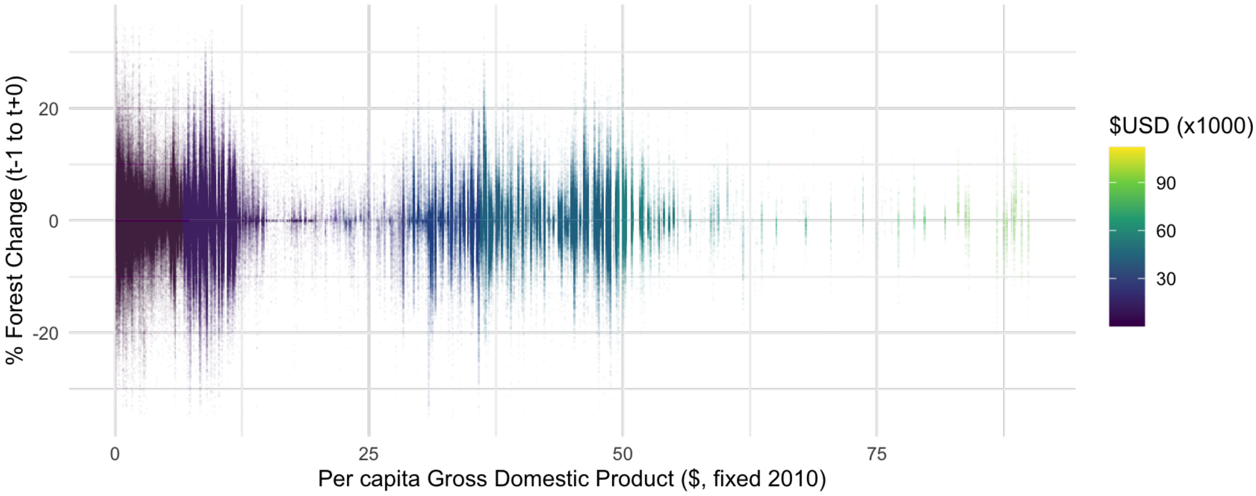
Levels of aggregation, a brief discussion. As political scientists increasingly seek to include various levels of aggregation in their analyses, this poses potential problems for internal validity. Lee and Rogers (2019) point out that determining the appropriate level of aggregation can be difficult and lead to different results, and hence validates further discussion. Here, the grid cell level has a fixed geographic area as the unit of analysis, and it tends to up-weight countries with lots of forests as each unique forested grid cells is weighted equally. The country level dependent variable, however, tends to up-weight the effects on forests in countries without much forest as all countries are given a single percentage point value. I argue, similarly to other studies using this approach (e.g. Defries, Rudel, Uriate, Hansen 2011, p. 178; Sandord 2021, p. 8), that deriving estimates with the satellite aggregated panel data is preferable, as it offers better quality of net forest change than the country-level data. The cell level data is also closer to the *actual* level of treatment, as a theorized national level change in regime (through democratization, or the introduction of a new support group) has local or provincial deforestation consequences.

A look at the dependent variable with some data. In figure 4.3 I display the forest change cells in a bivariate relationship with per capita GDP. What is notice-

[6] This variable is based on the Global Ecological Zones, a standard used by the United Nation's Food and Agricultural Organization (FAO) for dividing land use into different categories. The categories included in the tropical data set are: Tropical rainforest, subtropical mountain system, subtropical dry forest, tropical dry forest, tropical moist deciduous forest, tropical mountain system, subtropical humid forest and tropical shrubland.

able here is that most of the worlds forest change in the years 1982 to 2016 happened in countries with annual per capita GDP below $12,500, i.e. low- to middle-income countries. The cells in these countries also show a high degree of variability, meaning that there is both significant forest regrowth and forest loss.

Figure 4.3: Forest Cover Change (%) and Per Capita GDP, 1982 to 2016



This graph shows the distribution of 1,787,050 individual grid cells' percentage point forest change on an x-axis measuring GDP per capita (WB 2017).

4.2 Support Coalition Identity Data

The data set covering a polity's support coalition is derived from the definition of "political regime" mentioned in chapter 2, defining a political regime as the rules that are essential for selecting political leaders and for maintaining them in power (Djuve, Knutsen and Wig 2019, p. 927). In this regard, the make-up of the support coalitions in these regimes identify who gets to select policy.

The data covering the identity of the *support coalition* is presented in Knutsen et al. (2019) as an addition to the larger V-Dem dataset used in this paper (Coppege et al. 2021).[7] The data on contains information on 14 different 'support groups' who represents some form of unified class or common interest in a given society, the most important support group for the regime's survival as well as where the majority of a regime's supporters are located for the years 1789 to 2020. The data on these support groups were coded by a group of experts (social scientists) with knowledge of the country in question. According to Knutsen et al. (2019), about five experts are involved in coding each country for the period after 1900, as well as decisions being up for crowd-based reviews. To determine the identity of the different groups, the experts were presented with the 14-category scheme of a support coalition's potential support groups.

The 14 groups in the scheme includes various group categories such as urban middle classes, rural working classes, agrarian elites - and comparatively - urban middle classes, urban working classes and business elites.[8] This scheme is used to create various variables, and in this thesis I will use three of them: One multiple selection variable covering the different support groups ("v2regsupgroups"), pertaining to the coding question "Which groups does the current political regime rely on in order to maintain power?". The different groups in the coalition are coded as separate variables reflecting the mean coding choice by the experts on a continuous scale from 0 to 1 ("v2regsupgroups_x"), where all scores above 0.5 means that over half of the expert coders agreed on the presence of a certain support group in the coalition (I will return to these groups in section 4.2 and 4.3 of this chapter). Another single election variable covering the regime's most important group ("v2regimpgroup"), pertaining to the question "Which (one) group does the current political regime rely on most strongly in order to maintain power? ". The last relevant single selection variable covers the regime support coalition's overall location ("v2regsuploc"), pertaining to the question "In which geographic area do the support groups for the current political regime mainly reside?". According to Wig, Dahlum, Knutsen and Rasmussen (2020), to maintain the consistency in the understanding of the 'regime' concept and the

[7] See *Concepts*, in Chapter 2 for a more in-depth definition.

[8] Other notable groups are also included in the full scheme: Party elites, the military, state bureaucracy, religious- and ethnic groups, members of the aristocracy, religious groups, local elites (including customary chiefs), and foreign government or colonial powers.

particular regimes' identities, the experts were presented with concept clarification as well as pre-coded dates and name of each regime and as such, experts could then code support groups as time-varying features, also within regimes, down to the date level (Wig, Dahlum, Knutsen and Rasmussen 2020, p. 13). The information of the different regimes and their transitions is coded as the variable regime information ("v2reginfo").

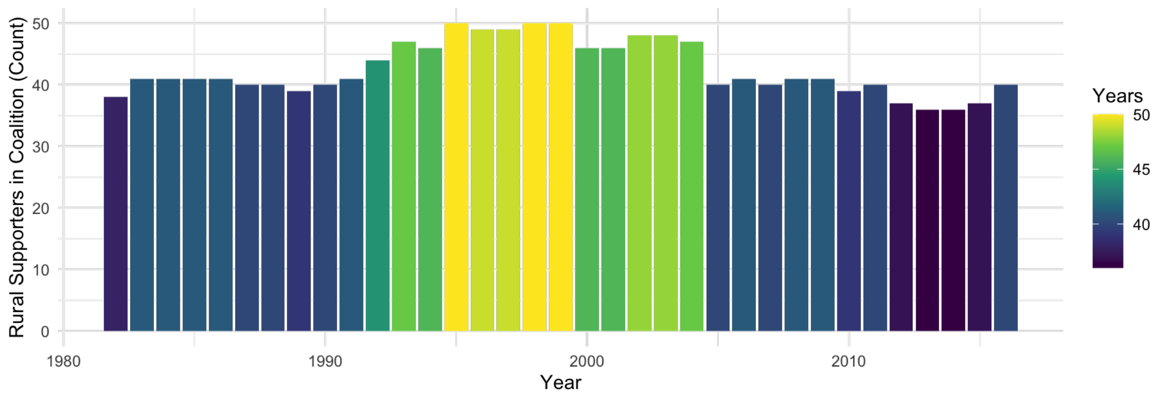
Reliability and internal validity. Expert surveys are powerful tools for measuring political concepts such as the characteristics of a support coalition. However, assigning values to underlying traits is complicated and experts will tend to exhibit varying levels of bias and reliability in their ratings of the different members of a support coalition. To better reliability, Gerring (2017) suggests crowd-based assessment and evaluation of the individual coder's decisions - a practice that the V-Dem data set has follows by having multiple coders for the same country and by discussing cases and uncertainties (Gerring 2017, p. 25-28). Still, there may be variation in the level of coder training and expertise on the cases, as well a bias in the process of selecting expert coders. Another potential caveat is that experts may disagree on assessments, and as such scholars should endeavor to capture the extent of disagreement to give a better estimate of uncertainty. This is especially important in projects where there are many expert coders, as the variation in individual coders influence how they perceive the survey scales (a phenomena called differential item functioning, or DIF) which in turn increases their rates of random error. As such, Marquardt and Pemstein (2018) argue that projects should include item-response theory (IRT) modelling to account for DIF and random errors stemming from variation in expert reliability (Marquardt and Pemstein 2018, p. 431-32). While the V-Dem data on support coalitions does not use IRT modelling for its coding, it attempts to model expert disagreement by taking the mean of the expert coded values for the individual support groups and aggregating them into a variable on a continuous scale. A potential problem for measurement validity is the way support groups in the support coalition are not coded as mutually exclusive, it can create problems in terms of measurement validity, as the member of the coalition the researcher is trying to capture may be correlated with another group. In this regard, robustness checks can mitigate some of the 'noise' created by the other groups in the coalition. Consequently, while reliability and measurement validity concerns exist, the V-Dem data allows scholars to give some estimate of coder disagreement and has attempted to mitigate reliability concerns through crowd-based assessments of cases.

4.2.1 Independent/interaction variables: Rural Supporters

My first set of interaction variables are two dummy-variables measuring the conceptualized rural groups in chapter 3, namely "rural support groups" and "agrarian elites."

Rural support groups. To measure the presence of rural supporters in the support coalition, I construct a dummy-variable is named "Ruralsup". This dummy is scored 1 for regimes that are supported by rural working class supports ("v2regsupgroups_11") and/or rural middle class supporters ("v2regsupgroups_12"), and 0 otherwise. These groups support groups reflect different rural interests, such as for example the peasantry (working class), or family farmers (middle class). These variables are meant to serve as a proxy reflecting the majority of non-elite rural supporters. The coded dummy draws on the multiple selection question on support groups with the original V-Dem variable being continuous from 0 to 1. I instruct R to keep the country- and cell-years where half or more (≥ 0.5) of the expert coders agree that there are rural groups in the support coalition, a relatively conservative cut-off. Lastly, I create another dummy for robustness checks addressing the geographic location of supporters ("v2regsuploc", see appendix A).

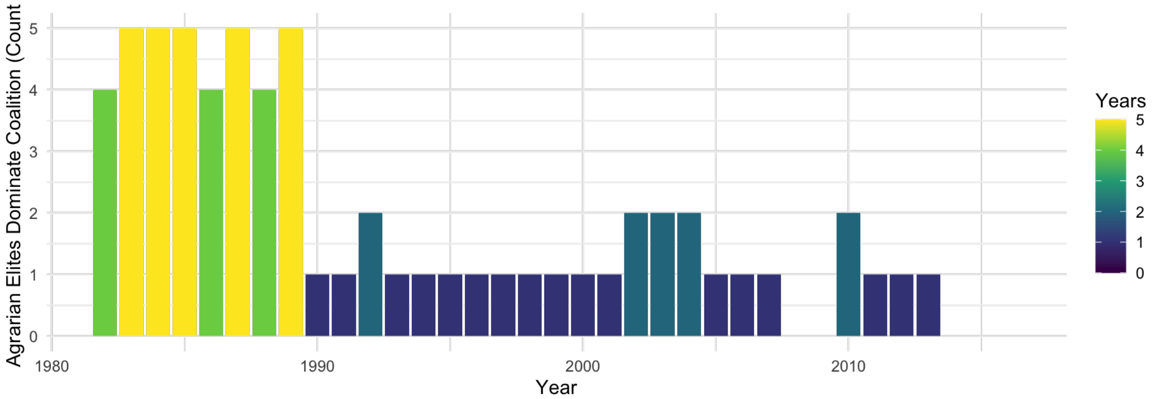
Figure 4.4: Rural Supporters in the Support Coalition, 1982 to 2016 (Count)



Looking at the pattern over time suggests that there has been a relatively even number of years where rural groups have been in the regime's support coalition between 1982 to 2016, with a slight declining trend since the 2000s. In total, these groups make up 510,590 years when aggregated to the cell level (cell-years), or 1,723 country-years.

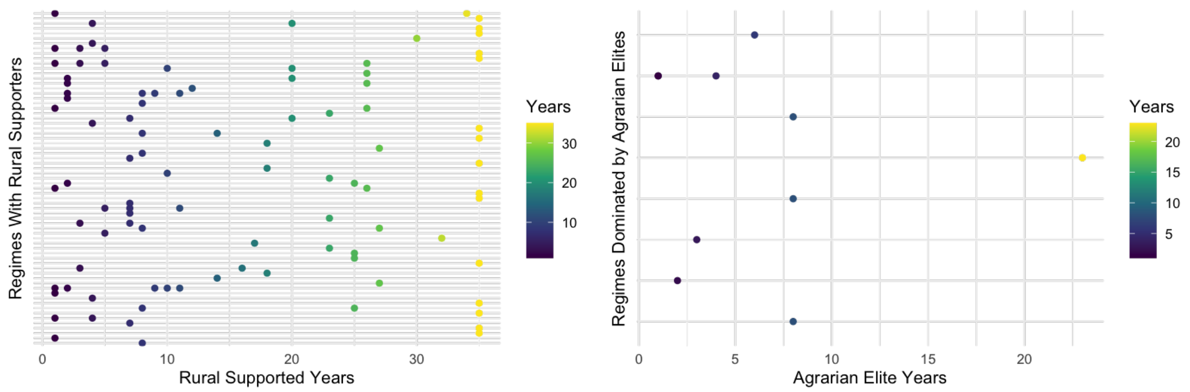
Agrarian elites. For the "extreme case" where agrarian elites dominate the support coalition, I construct a dummy-variable is named "Agrelite_mimp". This dummy is scored 1 for regimes where the most important group in the support coalition are agrarian elites, and 0 otherwise. This particular group is a proxy intended to measure rich peasants and large rural landholders that may cast an out-sized effect on land use. My dummy draws on the single selection question on most important group and the original V-Dem variable ("v2regimpgroup"). Below I have included a graphical representation of the total number of country-years with rural support coalitions and agrarian elites dominating the support coalition between 1982 to 2016.

Figure 4.5: Agrarian Elites Dominate Support Coalition, 1982 to 2016 (Count)



The time series shows that since 1982 there has been a decline in the number of years when agrarian elites dominate the support coalition. From the included groups in the data set that I analyse, the sample of agrarian elites is the smallest, as these groups only make up a total of 15,292 cell-years, or only 64 country-years.

Figure 4.6: Distribution of observations, rural supporters (year)



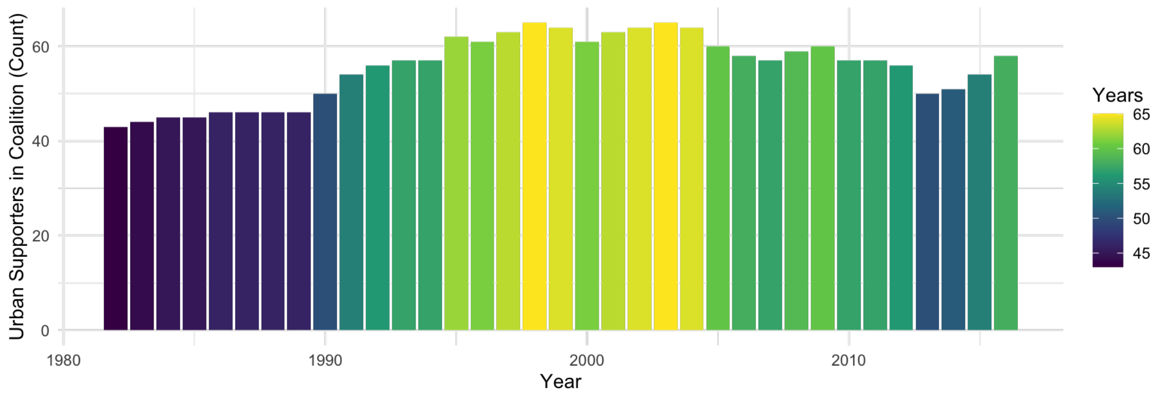
Next, figure 4.9 shows the distribution of years per regime. A regime could exist multiple times within the same country (e.g. after an election). Essentially, to study the effect that of different support groups have on forest change I am interested in seeing variation in the independent variable within the sample period (from 1982 to 2016). If all the regimes would exist for the 34 years of the sample, then it would not be possible to study the phenomena as there would be opportunities for comparison. As seen above, there is variation for rural supporters as well as agrarian elites, although the sample is limited.

4.2.2 Independent/interaction variables: Urban Supporters

My second set of interaction variables are two dummy-variables measuring the conceptualized urban groups in chapter 3, namely "urban support groups" and urban "business elites."

Urban support groups. The dummy-variable measuring presence of urban groups in a support coalition is called "Urbansup". Similarly to the rural groups, my dummy is scored 1 for regimes that are supported by urban working class supporters ("v2regsupgroups_9") and/or urban middle class supporters ("v2regsupgroups_10"), and 0 otherwise. These observations serve as a proxy for support groups that reflect different urban interests, such as for example urban factory/industrial workers and labour unions, as well as middle class groups such as non-industrial workers in the service sector and small-scale business owners. This reflects the majority of non-elite urban supporters. The coded dummy draws on the multiple selection question targeting support groups with the original V-Dem variable being continuous from 0 to 1. I follow the same coding rules as for the rural groups, instructing R to keep the country- an cell-years where half or more ($\geq$ 0.5) of the expert coders agree that there are urban groups in the support coalition. Similarly, as for the urban groups, I also create another set of dummy-variables for addressing geographic inclusion (see appendix A).

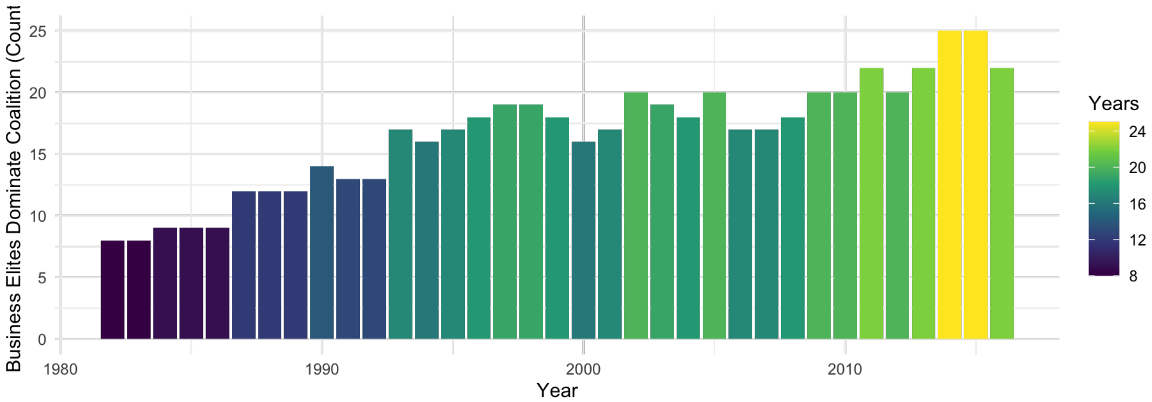
Figure 4.7: Urban Supporters in the Support Coalition, 1982 to 2016 (Count)



Eyeballing the time series in figure 4.7 suggests that there has been a relative increase in the number of urban groups from 1982 to 2016, although the growth has evened off in the mid-2000s. The urban support groups sample makes up a total of 813,278 cell-years, or 1,944 country-years.

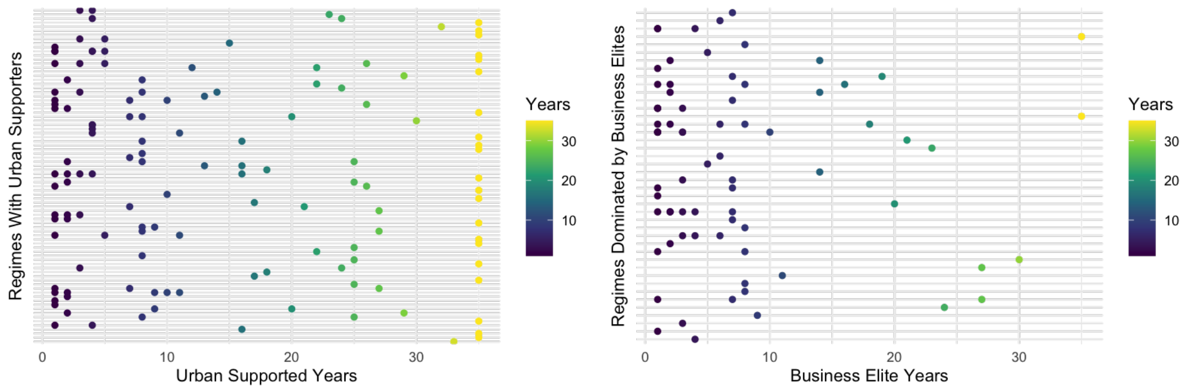
Business elites. As hypothesized in chapter 3, my second "extreme case" expectation is that rent-seeking business elites may have a particularly adverse effect on forest loss. To measure the presence of business elites dominating the support coalition, I construct a dummy-variable is named "Busielite_mimp". This dummy is scored 1 for regimes where the most important group in the support coalition are agrarian elites, and 0 otherwise. This particular group is a proxy intended to measure wealthy urban entrepreneurs, board members, shareholders or large business owners. My dummy draws on the single selection question on most important group in the support coalition (the V-Dem variable "v2regimpgroup"). Below is a representation of the number of country-years with business elites dominating the support coalition:

Figure 4.8: Business Elites Dominate Support Coalition, 1982 to 2016 (Count)



Looking at figure 4.8 covering the time series from 1982 to 2016, there has been a notable upwards trend in the count of years where business elites dominate the support coalition. The total time series makes up 92,219 cell-years, or 581 country-years.

Figure 4.9: Distribution of observations, urban supporters (year)



Similarly to the rural groups, figure 4.9 suggests that there is considerate variation in the samples for the two urban independent/interaction variables, making the data suitable for exploring changes in the values of the independent variables. Lastly, in table 4.1, I include a summary of the cell-years and country-years for the different support groups:

Table 4.1: Summary of Support Coalition Identity Variables

Variable	Cell-years	Country-years
Rural supporters	510,590	1,723
Urban supporters	813,278	1,944
Agrarian elites (most important)	15,292	64
Business elites (most important)	92,219	581

4.3 Democracy Data

Next, I describe my measurement of democracy that I use in this thesis. As mentioned in chapter 2, I follow Dahl (1971/1982), emphasizing free and competitive elections, as well as extensive suffrage pertaining to ensure "rule of the many" - *polyarchy.* To operationalize this, my main independent variable measuring democracy and democratization (transition to democracy), I employ the dichotomous measurement of democracy by Boix, Miller and Rosato (2013).[9] This measurement offers year-on-year coverage from 1800 to 2015 and covers a total 222 countries. BMR's designation of democracy draws inspiration from Dahl's 'thin' definition of democracy, taking into account a country's level of contestation and inclusiveness.[10] For BMR, the contestation criteria is considered fulfilled if a country's political system has (1) directly or indirectly elected executives in popular elections who are responsible either directly to voters or to a legislature, and (2) the legislature (or the executive if elected directly) is chosen in free and fair elections. In BMR, inclusiveness (or participation) is considered fulfilled if a majority of adult men are allowed to vote (Boix et al. 2013, p. 1530).

As touched upon in chapter 2, a 'thin' concept of democracy such as BMR's variable is more adaptable to different theoretical arguments. It emphasizes the *electoral* component of democracy, and therefore is better suited to explore the nexus between forest loss, democracy and economic development than a thicker concept of democracy. A thicker concept of democracy, such as some of the multidimensional aspects suggested by Coppedge et al. (2011),[11], would be problematic as the concepts would overlap the other socioeconomic or environmental variables used here, creating correlations between the right-hand side variables. Another advantage of using the BMR measurement is that it was constructed to be a dedicated dichotomous measurement of democracy. Most other measurements of democracy requires setting cut-offs which can yield arbitrary results when dichotomizing democracy and autocracy. Lastly, using the BMR measurement of democracy also facilitates easier comparison to Sanford's (2021) study, as well as replicability. However, a disadvantage of using a 'thin' and dichotomized measurement of democracy is that it offers a more stylized version of reality than what a 'thicker', continuous measurement of democracy does. In terms of measurement validity, BMR data is based on clear coding decisions and crowd-based assessments, meant to reduce overall concerns of reliability and measurement validity, but similarly to the V-Dem data does not employ IRT modelling. One notable weakness of BMR, is that it only takes into consideration whether a majority

9 I'll refer to this measurement as the BMR democracy measurement for the remainder of this thesis.

10 For an elaboration on Dahl's definition, see *Concepts* in Chapter 2.

11 For example, the data sets of the V-Dem project have attempted to captures other dimensions of democracy such as guaranteed civil liberies and constraints on the chief executive ("liberal democracy"), civil society participation and contestation of policy ("participatory democracy"), deliberation between politicians and citizenry ("deliberatory democracy), how well socioeconomic rights and inequalities in economic resources are measured ("egaliterian democracy").

of *adult men* are granted suffrage, as historical political units may be considered democracies even if women are not allowed suffrage in the country's political system. However, as my full data set starts in 1982, all democracies coded have universal suffrage.

4.3.1 Independent variable: Democracy (BMR)

The BMR measure is included in my full data sets as the variable "democracy_BX" and scores democratic country- and cell-years 1 if the country is coded as democratic, and 0 if the country is coded as autocratic. Given that my complete data sets cover country- and cell years from 1982 to 2016, it allows me to capture democracy in 4,875 country-year and 1,738,338 cell-years. The period following 1982 captures most of Huntington's (1991) 'third wave' of democratization as well new democracies in the 2000s and early 2010s, resulting in a total of 61 countries transitioning to democracy by 2016, offering global variation.[12] On the following page I have also included a table covering all the democratic transitions during this time period (table 4.1). In appendix B I also include a distribution of democratic country-years (in red) from 1982 to 2016.

[12] The complete total is 66 transitions, as some countries transition to democracy multiple times.

Table 4.2: Democratic transitions (BMR), 1982 to 2016

	Year	Country	Transition (v2reginfo)	Democracy (BMR)
1	1983	Argentina	Transition to democracy post-1983 (31/10/1983 - E)	1
2	1983	Thailand	1977-1988 Period of strengthened parliament (21/10/1977 - 24/07/1988)	1
3	1983	Turkey	Post-1982 constitutional Republic of Turkey (08/11/1982 - 16/04/2017)	1
4	1984	El Salvador	Civil war administrations (21/12/1983 - 01/06/1994)	1
5	1984	Nicaragua	The Sandinista regime (18/07/1979 - 25/04/1990)	1
6	1985	Brazil	"New Republic" (22/04/1985 - 05/10/1988)	1
7	1985	Uruguay	Post-1985 return to civilian rule (02/03/1985 - E)	1
8	1986	Guatemala	Semi-civilian government post 1986 (15/01/1986 - 25/05/1993)	1
9	1986	Philippines	Post-Marcos transition (26/02/1986 - 02/02/1987)	1
10	1986	Sudan	Return to parliamentary rule 1986-1989 (07/05/1986 - 30/06/1989)	1
11	1988	Pakistan	Elected government 1988 - 1993 (03/12/1988 - 18/07/1993)	1
12	1988	South Korea	The Sixth Korean Republic (30/10/1987 - E)	1
13	1988	Suriname	Interlude 1987-1990 (01/10/1987 - 24/12/1990)	1
14	1989	Poland	Post-Communist Poland - the third Republic (05/06/1989 - 02/04/1997)	1
15	1990	Bulgaria	People's Republic of Bulgaria (05/12/1947 - 12/07/1991)	1
16	1990	Chile	Republic of Chile (12/03/1990 - E)	1
17	1990	Hungary	Post-Communist Hungary (24/10/1989 - 01/01/2012)	1
18	1990	Mongolia	Post-communist transition (16/04/1990 - 12/02/1992)	1
19	1991	Bangladesh	1990-2007 alternation of governments (21/03/1991 - 12/01/2007)	1
20	1991	Benin	Benin under 1990 constitution (05/04/1991 - E)	1
21	1991	Nepal	Constitutional monarchy restored - 1990 (10/11/1990 - 04/10/2002)	1
22	1991	Panama	Transitional government under Endera (21/12/1989 - 01/09/1994)	1
23	1991	Romania	Republic of Romania (09/12/1991 - E)	1
24	1991	Sao Tome and Principe	Post-1991 alternation (04/04/1991 - E)	1
25	1991	Sri Lanka	The Democratic Socialist Republic of Sri Lanka (08/09/1978 - 12/11/1994)	1
26	1991	Suriname	Post-1991 alternation (17/09/1991 - E)	1
27	1992	Albania	Post-1992 Albania (10/04/1992 - E)	1
28	1992	Guyana	Post-1992 alternation (10/10/1992 - E)	1
29	1992	Lithuania	Republic of Lithuania (26/11/1992 - E)	1
30	1992	Mali	Republic of Mali - post- 1992 democratic interlude (13/01/1992 - 22/03/2012)	1
31	1992	Russia	Post-Soviet Russia (01/01/1992 - 21/09/1993)	1
32	1992	Thailand	First democratic period (25/05/1992 - 11/10/1997)	1
33	1993	Central African Republic	Multiparty rule, Patassé's presidency (23/10/1993 - 15/03/2003)	1
34	1993	Latvia	Independent Latvia (22/08/1991 - E)	1
35	1993	Madagascar	The Third Malagasy Republic (20/08/1992 - 17/03/2009)	1
36	1993	Niger	Democratic interlude in Niger (23/01/1993 - 21/01/1996)	1
37	1994	Guinea-Bissau	Vieira's rule (15/11/1980 - 07/05/1999)	1
38	1994	Malawi	Malawi since 1993 constitution (17/05/1994 - E)	1
39	1994	Mozambique	Independent Mozambique - Frelimo rule (26/06/1975 - E)	1
40	1994	South Africa	Post-Apartheid transitional period (28/04/1994 - 04/02/1997)	1
41	1997	Albania	Post-1992 Albania (10/04/1992 - E)	1
42	1997	Ghana	Rawlings' rule (01/01/1982 - 07/01/2001)	1
43	1999	Indonesia	Post-Suharto transition (22/05/1998 - 10/08/2002)	1
44	1999	Niger	Tandja's government (19/07/1999 - 26/06/2009)	1
45	2000	Croatia	Independent Croatia (22/11/1995 - E)	1
46	2000	Mexico	Post-single party Mexico (03/07/2000 - E)	1
47	2000	Senegal	Post-Socialist Party Senegal (02/04/2000 - E)	1
48	2001	Peru	Constitutional and alternating governments since 2001 (29/07/2001 - E)	1
49	2002	Kenya	Constitutional alternation of presidents since 2002 (31/12/2002 - E)	1
50	2002	Sierra Leone	Post- 1998 restored civilian rule (11/03/1998 - E)	1
51	2003	Ecuador	Post- 1979 constitutional rule (11/08/1979 - E)	1
52	2003	Paraguay	Republic of Paraguay (21/06/1992 - E)	1
53	2004	Georgia	Post-Rose Revolution Georgia (24/11/2003 - E)	1
54	2005	Burundi	Post-2005 constitution (01/03/2005 - 28/06/2010)	1
55	2006	Liberia	Republic of Liberia (19/01/2006 - E)	1
56	2006	Solomon Islands	Solomon Islands under RAMSI (25/07/2003 - 30/06/2017)	1
57	2008	Nepal	Democratic republic of Nepal (29/05/2008 - E)	1
58	2008	Pakistan	Alternation post-2008 (19/08/2008 - E)	1
59	2008	Zambia	Zambia since 1996-amendments (17/05/1996 - E)	1
60	2009	Bangladesh	2008-2014 constitutional alternation (07/01/2009 - 05/01/2014)	1
61	2010	Honduras	Return of constitutional rule (28/01/2010 - E)	1
62	2011	Niger	Post-2011 constitutional rule (08/04/2011 - E)	1
63	2011	Thailand	PPP rule (24/12/2007 - 22/05/2014)	1
64	2014	Fiji	Bainimarama's constitutional rule (08/09/2013 - E)	1
65	2015	Nigeria	Post- 1999 alternation (30/05/1999 - E)	1
66	2015	Tunisia	Interim constitution (27/01/2014 - E)	1

4.4 Control variables

In order to reduce the risk of the estimated effects being spurious, that is, that they are driven by confounding variables, control variables will be incorporated in the model. These controls are sourced from the World Bank's *World Development Indicators* data set (WB 2017). I lagged these variables as to present 'post-treatment' controls, hence per capita GDP is included from time t - 1, per capita GDP and population growth is included as the change from time t - 2 to time t -1 as well. All of the World Bank control variables are on the country-level, and as such aggregated down to the grid cell level, meaning that each cell within a country is given the country-level value of the given control variable.

GDP per capita, lagged t-1 ($USD). As environmental economists and political scientists have hypothesized that the size of economic activity affects forest loss , this presents a relevant confounder that needs to be controlled for to make unbiased estimates. I therefore include GDP in per capita numbers in fixed 2010 thousands of US dollars, a metric measuring the total monetary or market value of all the finished goods and services produced within a country's borders for a specific time period divided by the total population for the same time period. As such, this control variables offers a measurement of economic activity at a particular time adjusted for its population size. For 2010, the mean global per capita GDP is $ 10'664 for the country-year data set. The data's corresponding code in the World Development Indicators data set is NY.GDP.PCAP.KD. I have followed Sanford (2021) here for comparability, but including a linear version of per capita GDP is considered controversial in the economics literature, so for robustness checks in section 5.3 I also employ a log-transformed version of the same variable. Logarithm transformation can change a highly skewed variable into a more normalized distribution (Kim 2022). In this case it centers the distribution of the control variable on the dependent variable. These tests can be found in appendix A.

Δ GDP per capita, lagged t-2 to t-1 (% change). Similarly to the above, delta GDP per capita also offers a metric of economic activity adjusted for population size, but gives an indication of year-on-year change in economic activity. Delta refers to change in percentage points from previous year. As explored in chapter 2, economic growth has been theorized to have an adverse affect on forests (for example, Chupezi 2009), and is therefore another important confounder that needs to be controlled for. The data's corresponding code in the World Development Indicators data set is NY.GDP.PCAP.KD.ZG.

Δ Population growth, lagged t-2 to t-1 (% change). As mentioned in chapter 3, scientists have shown that population growth and growing demand for land presents another potential driver of deforestation (e.g. Defries, Rudel, Uriate, et al. 2010), making another confounder that needs to be included in the regression to reduce estimation bias. The mean population growth rate for all years (1982-2016) is 1.657%. The data's corresponding code in the World Development Indicators data set is SP.POP.GROW.

Forest Cover, t-1 (%). Lastly, I also follow Sanford's (2021) design and include lagged forest as a control variable, namely the percentage of forest cover in a given cell last year. This controls for the amount forest remaining in a cell at the start of the year as I expect deforestation rates might be higher in places that are partially forested compared to grid cells with near 100% forest cover.

4.5 Model Selection

So far, I have outlined the data I will use for my analysis. I end up with a slightly unbalanced data set (summary statistics are reported in appendix B). In this section I present the models I will use. From the data presented above, my goal is to conduct a comparative large-N study, and study how the variation in regime supporters may moderate the effect of democracy. Large-N studies are more likely to encounter variation in the key variables that we are interested in, giving it an advantage to small-N studies (Bryman, 2016, p. 53). The two different statistical models I will use in this thesis. For my main analysis, I use a two-way fixed effects estimator. As part of the robustness checks, I also use a new difference-in-difference estimator for panel data matching introduced by Imai, Kim and Wang (2021). Below I describe these methods in detail, and their particular advantage for investigating the outlined hypotheses and assumptions.

4.5.1 Ordinary Least Squares With Two-Way Fixed Effects

To test the posited hypotheses, I will use ordinary least square (OLS) regressions for panel data with both unit and time fixed effects, often called the "two-way fixed effects" estimator (TWFE). The TWFE model builds on OLS, a common regression modelling strategy used in social science where a linear relationship is estimated by minimizing the sum of squared errors (Stock and Watson 2007, 118). Adding unit fixed effects to OLS ignores the possibility that unit-to-unit variation will shed a light on the theorized relationship, and instead focused on within unit variation following an intervention (in my case, the change in the value of the dummy variables). For this reason, the unit fixed effects estimator is also called the *within estimator*. Adding year fixed effects to the within estimator controls for global level changes that can have the same effect for all the units, constituting the TWFE model (Wooldridge 2021, p. 2).

Given that the cause of forest cover change in each grid cells have omitted variables that are relatively constant over time, but vary across cells (country-specific factors), as well as having omitted variables that are constant for all of the cells but vary over time (such as global commodity prices) I consider it appropriate to use TWFE (Stock and Watson 2015, p. 409). The idea is to let the value of these omitted variables be similar across time, yet vary between the years before and after an assigned intervention. I my case the intervention is a change in the year-dummies for democracy and the different support groups. Using fixed effects is therefore a relatively common way to control for omitted variables that can be difficult to operationalize (Christophersen 2018, p. 171), or cannot be observed directly due to lacking data.

Considering the above, I deem it appropriate to follow the modelling strategy of Sanford (2021), including unit fixed effects on the cell level is intended to absorb omitted variable bias arising from time-invariant characteristics at the cell level such as soil type, average climate, elevation, and other idiosyncratic factors. Additionally, year fixed effects are included to absorb unobserved global-level economic changes for a particular year, such as changes in the price of timber, food and fuel that have an effect on forest cover.[13]

Assumptions. First, all use of OLS assumes that the relationship between the dependent and independent variable is linear. Second, the error is uncorrelated with all observations of the variables for the units over time. If this assumption is violated, we face omitted variables bias as the explanatory variables that are included is assumed to not correlate with any omitted explanatory factors. This is an assumption that is difficult to satisfy in social science without some form of randomization, putting pressure on the researcher to explore alternative explanations for their findings or provide 'thicker' contextual knowledge about the subject at hand (Coppedge 2012, p. 265-66). I have attended to probe for alternative explanations using various robustness tests presented in section 5.3.

Third, an important assumption for the TWFE model and OLS regression in general is that there is no perfect multicollinearity, meaning that several independent variables in a model are correlated with one another. High multicollinearity can lead to incorrect significance values, greater variance and insufficient estimates, thus making it difficult to detect significant effects (Christophersen, 2018, p. 76). To account for this, I conduct several Variation Inflation Factor (VIF) tests that measure multicollinearity of the model specifications. It allows rapid measuring of how much a variable is contributing to the standard error in the regression. When significant multicollinearity issues exist, the variance inflation factor will be very large for the variables involved. All VIF tests are reported in appendix D.

Lastly, TWFE model assumes that variables for one unit are distributed identically to, but independently of, the variables for another unit, meaning that all observations are sampled from the same population and should have the same sampling variance.[14] In my case, the data hierarchical and clustered within countries, and thus varies with groups in the sample. As Abadie, Athey, Imbens and Wooldridge (2017) point out, clustering standard errors is justified when the assignment mechanism is clustered and varies systematically with groups in the sample. As such, I deem it appropriate to cluster standard errors on the country level and on years to account for autocorrelation in the residuals between cells in the same country, potentially across many years and to account or cor-

[13] I also include robustness checks with the country-level dependent variable, where fixed effects is introduced on the country-level.

[14] Variance is a measurement of dispersion, pertaining to the expected value of the squared deviation of a random variable.

relation in residuals between distant cells in the same year.[15]

Given the relatively large number of operations needed to model fixed effects and clustered standard errors for the grid cells, I use the 'lfe' (linear group fixed effects) package in R by Cameron, Gelbach and Miller (2012). This package is suitable for regression analysis with large panel data (above a million observations), while still allowing for multiple-group fixed effects and clustered standard errors. Using 'lfe' comes with some limitations, as it does not allow for negative weights, limiting the possibility of using weighted least squares (WLS) as a robustness check in this thesis.

4.5.2 Mahalanobis Distance Matching With Panel Data

I run robustness tests in section 5.3 on the country-level to see whether the findings from the tests in section 5.1 and 5.2 are valid across different levels of aggregation. To do this I employ a new panel matching method by Imai, Wang and Kim (2021). One of the key motivations of using for using the Imai et al. (2021) method in thesis is that the method particularly suitable for estimating casual effects using data with not very long time periods. As the Song et al. (2018) data set only covers forest change from 1982 to 2016, panel matching offers the most statistical leverage for the data limitations for the country level analysis. While I am not looking for causality per se, I am interested in probing for potential associations that can be interpreted causally, yet I respect that this is difficult given the many potential sources of bias.

Matching offers some advantages in comparison to TWFE, which rely on difficult to uphold parametric assumptions such as linear additive effects, making it difficult to intuitively understand how counterfactual outcomes are estimated (Imai and Kim 2021, p. 405). Matching is a quasi-experimental technique that allows scholars to specify counterfactual outcomes more precisely, mimicking true experimental design where one group of units are assigned the treatment and the other group are kept as the control group (Rubin 2006). Additionally, matching can help ease some of the problems related to model dependence, the phenomena where different models fit the data about equally well, allowing for the scholars discretion to bias the presented results (King and Nielsen 2019, p. 436).

However, pre-existing matching methods have had limitations for use with time-series data (for example, Iacus, King, and Porro 2011). A possible – and popular – solution that has been frequently used in political science research the last ten years is the *synthetic control method*, such as Abadie et al. (2010) method or Xu's (2017) interactive effects estimator. In short, these methods allow for the inference with time-series data, but require a large number of control units that do not receive the treatment at all and

[15] These standard errors are often referred to as heteroskedasticity- and autocorrelation-consistent standard errors (HAC).

assumes the treatment status never reverses, making it unsuitable to investigate questions in relation to regime changes (as some countries experience many transitions, i.e. repeated autocratic reversal and democratization). For this purpose, Imai et al. (2021) introduces a new method allowing several types of matching algorithms to be used with time-series data, available through the 'panelmatch' package for R.

'Panelmatch' works by utilizing an algorithm that creates a set of control observations based on the user's instructed parameters in R. The algorithm finds units in similar time periods that have an identical treatment history for a determined time span. In my case, the algorithm searches for countries experiencing a democratic transition. After identifying potential matching, these matches can be further refined by assigning weights to the different matches by, for instance, matching on the control variables of individual observations. To estimates both short-term and long-term average treatment effects of the treated (ATT), the 'panelmatch' package uses a difference-in-difference (DiD) estimator that adjusts for a possible time trend, however, with slightly less stringent criteria for the parallel trends assumption due to matching on units *across* time.[16] The DiD estimator calculates the difference in average outcome in the treatment group before and after treatment minus the difference in average outcome in the control group before and after treatment.

The matching method I choose to use is Mahalanobis distance matching (MDM), as my treatment variables are binary (democracy and support groups) and I intended to control for various variables (per capita GDP and population growth). Including these give my test the resemblance of a blocked experiment (not a randomized experiment) where treated and control groups are blocked at the start exactly on the observed covariates. This gives MDM an advantage over other popular matching techniques such as propensity score matching, which assumes that treatment is assigned completely randomly giving biased estimates (King and Nielsen 2019, p. 435). Briefly explained, the Mahalanobis distance reflects the relative distance between single observations and a larger distribution in a multivariate space a measure. The 'panelmatch' algorithm uses this distance to assigns weights to matches based on certain criteria. Consequently, it creates a matched data set for analysis and matches the treated unit (in my case, countries) with untreated units based on the closeness of the control variables and assigns weight to the best matches.

The robustness of this estimates depends on the balance of the covariates. Covariate balance is the degree to which the distribution of covariates is similar across levels of the treatment. It has three main roles in causal effect estimation using matching: 1) as a target to optimize with matching, 2) as a method of assessing the quality of the resulting

[16] In a classical difference-in-difference design, the parallel trends assumption requires that in the absence of treatment, the difference between the 'treatment' and 'control' group is constant over time.

matches, and 3) as evidence to an audience that the estimated effect is close to the true effect (Greifer 2022). Another possible avenue to better estimates is by bootstrapping, which the 'panelmatch' package allows for. Bootstrapping is a type of re-sampling, where simulated draws from the original data is used to sample distributions. By repeating simulated draws, more robust estimates can be drawn as the scholar has a better idea of the distributions variance.

Chapter 5

Empirical Analysis

In this chapter, I present the empirical analysis of the data. The aim of the empirical analysis is to test the outlined hypotheses in chapter 3, using the data and methods outlined in chapter 4. In section 5.1, I test hypotheses 1 (**H1**), whether the presence of certain support groups moderates the effect of democracy found by Sanford (2021) across forests globally since 1982 and summarize the findings in section 5.1.1. Next, in section 5.2 I test hypothesis 2 (**H2**), whether certain support coalition identities have an effect on forest cover change. Further, in section 5.3, I run various robustness checks to see whether the findings in the previous sections hold up to various model specifications, as well as test the significant findings using the country-aggregated dependent variable using Mahalanobis distance matching. Lastly, in section 5.4, I assess the validity of the findings in light of the robustness tests and discuss the limitations of the modelling strategy used in this thesis.

As discussed in the previous chapter, the models in section 5.1 have all have fixed time- and unit effects to account for within unit variation. Additionally, the reported models also have HAC consistent standard errors, being clustered standard errors. Introducing clustered standard errors significantly reduces the number of active observations in the regression. In section 5.3, For the Mahalanobis distance models presented in section 5.3 I also report the covariate balance for the different models.

5.1 Democracy, support groups and forests (0.5° cells)

Table 5.1 displays my baseline interaction models, testing **H1** - whether the effect of democracy on forest change is moderated by the incumbent regime's support coalition. These models test whether grid cells within a country experienced more forest change under democracy than under autocracy, moderated by the four different support groups outlined in chapter 4. This effectively targets within-country forest change for the 61 countries that transition from autocracy to democracy in the time period between 1982 to 2016. The dependent variable measures change in forest cover in percentage points in each grid cell from t-1 to t+0. This gives an estimate of forest change after both natural, economic and demographic drivers (forest in previous year, per capita GDP, growth in per capita GDP, and population growth) have been taken into consideration at t-1. The equation for the specifications targeting this relationship is presented below:

$$\mathbf{ForestChange_{i,t}} = \alpha_{\mathrm{i}} + \gamma_{\mathrm{t}} + \beta_1 * \mathit{Democracy}_{\mathrm{c,t}} + \beta_2 * \mathit{SupportGroup}_{\mathrm{c,t}} + \beta_3 * (\mathit{Democracy}_{\mathrm{c,t}} * \mathit{SupportGroup}_{\mathrm{c,t}}) + \lambda * \mathit{Controls}_{\mathrm{i,t\text{-}1}} + \epsilon_{\mathrm{i,c,t}}$$

Here, β_3 is the coefficient for the interaction element, targeting cell forest change under democracy moderated for a support group. α and γ represent cell and year fixed effects. λ is a vector for the control variables on the cell level at t-1. Lastly, ϵ denotes the residual value, or the unexplained variation of the model, which is clustered at the country and year level (c,t) to account for heteroskedasticity and autocorrelation.

Before running my interaction models, I first replicate the finding of Sanford (2021) indicating that forested cells within the same country under democracy is associated with higher-than-average global forest loss (-1.047%) than for autocracies, significant at the 0.05 level (M1 Sanford 2021) seen in table 5.1.[1] Next, my first interaction model (M2 Ru) targets forest change in a rurally supported democracy. For all the interaction models, the substantively important coefficient to watch is the interaction coefficient (β_3) given the use of binary variables. In M2 Ru, the β_3 (*Democracy x Rural supporters*) shows a significant positive effect on forest change at the 0.05 level, meaning that when rural groups were in the incumbent regimes support coalition, democracy was om average associated with 1.713% *reforestation* (forest growth) during the years 1982 to 2015. The next model, M3 Ur, tests whether democracies with urban groups in the support coalition are associated with forest change. The F-statistic for M3's β_3 (*Democracy x Urban supporters*) reports null results, meaning that democracy was not significantly associated with greater forest loss when moderated for urban groups although the statistic is trending towards forest loss (-0.393%). Model 4, (M4 Ae) tests whether democracy is associated with forest change when moderated for agrarian elites. Surprisingly, given the assumption that when

[1] Replicated using data on the 0.5° grid cell level. Sanford uses the higher resolution data (see chapter 4.1), but the results remain consistent.

agrarian elites dominate the support coalition, the F-statistic for M4 Ae, β_3 (*Democracy x Agrarian elites*), report back null results, however trending towards forest loss (-1.335%). lastly, model 5 (M5 Be) tests whether democracy is associated with forest change when urban business elites dominate the support coalition. Interestingly, despite the expectation of the rent-seeking behaviour of these groups, the F-statistic for β_3 (*Democracy x Business elites*) this model also report back null results with the coefficient trending toward forest growth (0.932%), meaning that democracy was not significantly associated with greater forest loss when these elites dominate the support coalition. Moving on to the control variables, for all the models, the coefficient for forest t-1 control reports back significant results at the 0.001-level. This is expected as forest cells in previous years inhibit similar characteristics to the cells in the current year.

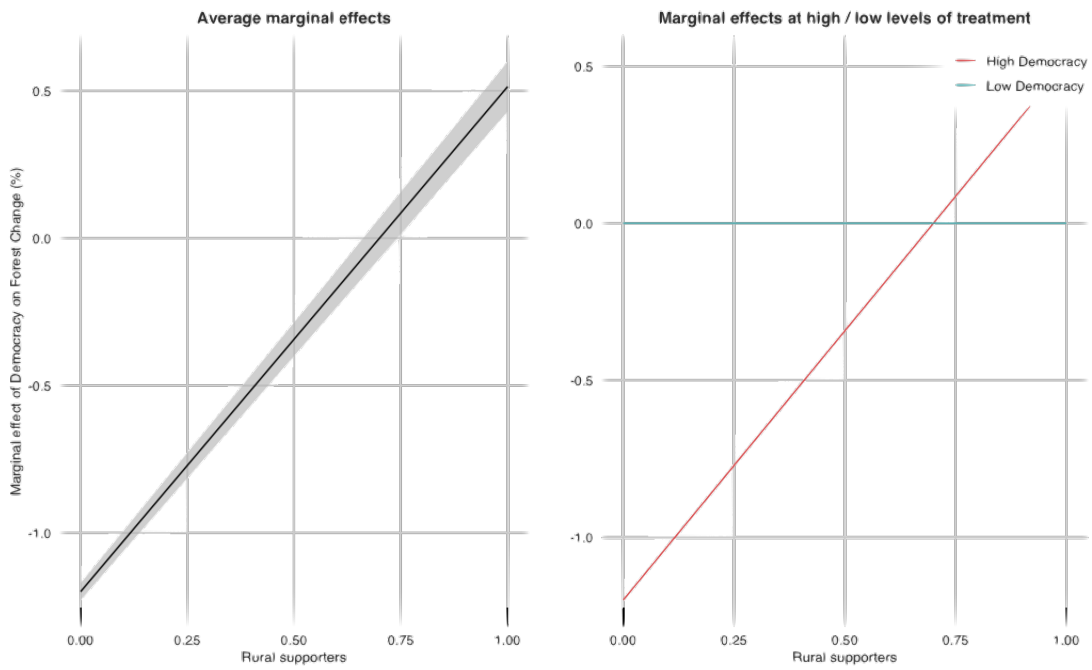
Table 5.1: Interaction models (1): Democracy, support groups & global forests (TWFE)

	Dependent variable:				
	Forest change % (t-1 to t+0)				
	(M1 Sanford 2021)	(M2 Ru)	(M3 Ur)	(M4 Ae)	(M5 Be)
Democracy (BMR)	−1.047* (0.405)	−1.199** (0.414)	−0.660 (0.396)	−1.034* (0.404)	−1.088** (0.372)
Rural supporters		−1.344** (0.491)			
Democracy x Rural supporters		1.713* (0.689)			
Urban supporters			−0.191 (0.772)		
Democracy x Urban supporters			−0.393 (0.905)		
Agrarian elites (mimp)				0.946 (1.364)	
Democracy x Agrarian elites (mimp)				−1.335 (1.324)	
Business elites (mimp)					−1.808** (0.634)
Democracy x Business elites (mimp)					0.932 (0.551)
Per capita GDP (t-1)	0.060 (0.037)	0.062 (0.037)	0.063 (0.037)	0.061 (0.037)	0.057 (0.036)
Δ Per capita GDP (t-1)	−4.638 (15.486)	−7.788 (15.135)	−8.184 (13.936)	−4.450 (15.502)	−9.712 (16.032)
Δ Population growth (t-1)	−0.131 (0.190)	−0.104 (0.193)	−0.149 (0.179)	−0.128 (0.190)	−0.114 (0.188)
Forest (t-1)	−0.655*** (0.043)	−0.656*** (0.043)	−0.655*** (0.043)	−0.655*** (0.043)	−0.656*** (0.043)
Observations	1,545,318	1,545,318	1,545,318	1,545,318	1,545,318
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes	Yes
R^2	0.365	0.366	0.366	0.365	0.367
Adjusted R^2	0.343	0.344	0.344	0.343	0.345
Residual Std. Error	3.844 (df = 1493735)	3.842 (df = 1493733)	3.843 (df = 1493733)	3.844 (df = 1493733)	3.840 (df = 1493733)

Note: *p<0.05; **p<0.01; ***p<0.001

In figure 5.1 I present a marginal effects plot for model 2 (M2 Ru), targeting the marginal effect of democracy when rural supporters are in the support coalition. Marginal effect plots are helpful for interpreting interaction effects as it tells us tells us how a dependent variable (grid cell forest cover change) changes when a specific independent variable changes (in this case rural supporters). What is noticeable here is the moderating effect that rural support groups have on democracy's effect on forest change, flipping the β_3 in a positive direction. Another noticeable aspect about the plot is that the standard errors increase with the introduction of the rural groups (from 0.414 to 0.689), as illustrated by the widening of the shaded 95% confidence interval (CI):

Figure 5.1: Marginal Effect of Democracy on Forest Cover Change (95% CI)



Next, in table 5.2, I run similar tests on the reduced sample only including tropical forests. These forests are filtered from the grid cells based on the FAO's designation of ecological zones.[2] As mentioned in chapter 4, these forest have a particularly large biomass, giving them an important role in mitigating climate change (or contrary, can exacerbate climate change if deforested by releasing more carbon dioxide into the atmosphere when deforested). Similarly, in M1 I begin by replicating Sanford's model, by regressing democracy directly on tropical forest change with controls. Interestingly, this returns null results, meaning tropical forest cells under democracy was not associated with significantly greater forest loss than under the old autocracy. Addressing the interaction coefficient (β_3) for the other specifications, targeting the interaction between democracy and the support groups (M2T Ru, M3T Ur, M4T Ae and M5T Be), the coefficient trends remain somewhat similar, however the F-statistics suggests that democracy is not significantly associated with

[2] For the types of forest included as 'tropical', see chapter 5.1.1.

greater tropical forest loss when moderated for the different support groups. Similarly to the specifications targeting global forest loss, the F-statistic for forest (t-1) control reports back as significant for the tropical forest models.

Table 5.2: Interaction models (2): Democracy, support groups & tropical forests (TWFE)

	Dependent variable:				
	Forest change % (t-1 to t+0)				
	(M1T)	(M2T Ru)	(M3T Ur)	(M4T Ae)	(M5T Be)
Democracy (BMR)	−0.399	−0.463	−0.323	−0.357	−0.600
	(0.361)	(0.396)	(0.315)	(0.341)	(0.428)
Rural supporters		−1.150			
		(0.592)			
Democracy x Rural supporters		0.881			
		(0.699)			
Urban supporters			−0.779		
			(0.492)		
Democracy x Urban supporters			0.240		
			(0.586)		
Agrarian elites (mimp)				1.240	
				(1.716)	
Democracy x Agrarian elites (mimp)				−1.904	
				(1.608)	
Business elites (mimp)					-1.450^{*}
					(0.589)
Democracy x Business elites (mimp)					1.187
					(0.656)
Per capita GDP (t-1)	0.031	0.032	0.033	0.033	0.025
	(0.053)	(0.054)	(0.053)	(0.053)	(0.054)
Δ Per capita GDP (t-1)	−47.969	−47.639	−47.124	−47.994	−47.759
	(27.110)	(26.924)	(27.253)	(26.936)	(26.842)
Δ Population growth (t-1)	−0.190	−0.172	−0.225	−0.182	−0.131
	(0.302)	(0.304)	(0.284)	(0.302)	(0.292)
Forest (t-1)	-0.625^{***}	-0.626^{***}	-0.627^{***}	-0.626^{***}	-0.626^{***}
	(0.052)	(0.052)	(0.052)	(0.052)	(0.053)
Observations	542,137	542,137	542,137	542,137	542,137
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes	Yes
R^2	0.362	0.363	0.363	0.362	0.363
Adjusted R^2	0.342	0.342	0.342	0.342	0.343
Residual Std. Error	4.169 (df = 525270)	4.167 (df = 525268)	4.166 (df = 525268)	4.167 (df = 525268)	4.166 (df = 525268)
Note:					*p<0.05; **p<0.01; ***p<0.001

To check for potential multicollinearity, where several independent variables in a model are correlated, I run a Variance in Factor (VIF) test. As noted, high multicollinearity can lead to incorrect significance values, greater variance and insufficient estimates, thus making it difficult to detect significant effects (Christophersen, 2018, p. 76). The VIF test returns VIF < 2 for all the above models, meaning that there is low correlation between the independent variables and that the OLS assumption of no perfect multicollinearity is met (see appendix D). The tests were all run without interaction terms, as with interaction terms the VIF test will not yield interpretable results. To check whether these findings overlap with other measurements of democracy, I replicated the above models using the

V-Dem Polyarchy measurement of democracy (Coppedege et al. 2021, can be found in appendix A), and it returns similar results.

5.1.1 Summary and interpretation of results

The above analysis suggests that the effect of democracy is moderated by identity of the regime's support coalition. Hence, I argue that I find support for **H1**. Among the different groups, I find support for hypothesis *H1a* suggesting that rural supporters decrease the marginal effect of democracy on forest loss. When rural supporters are present in the incumbent democratic regimes' support coalition the average forest change rate is positive (1.713%) - meaning that *reforestation* occurred after democratization. In light of theory, this can imply that the political enfranchisement of rural supporters may improve forest management, as suggested by Klooster and Masera (2000). Interestingly, when agrarian elites, urban supporters or urban business elites where interacted with democracy, democracy did *not* have a significant effect on forest cover change. Moreover, the direction of the interaction terms' coefficients all suggest a decrease in the marginal effect of democracy on forest loss, contrary to the expectations I outlined in hypothesis *H1b*, *H1c* and *H1d*. As such, I do not find support for these hypotheses. When addressing the tropical forest sub-sample, the interaction terms all yield null results, suggesting that democracy does not have a significant effect on tropical forest loss. This is interesting, given that much of the case study literature focusing on the adverse effects of democracy often focuses on deforestation in tropical countries. However, these tests come with limitations, as this sample only captures the 61 countries that transition to democracy in the period between 1982 and 2016. Yet, I argue that this is justified in order to study the potential different effects that democracy has across countries with different support coalitions.

However, as I argued in chapter 3, it might be possible that the effect of support groups is equal across democracies and autocracies. I therefore probe for the total effect that support coalitions have on forest cover change. Such tests would also allow me to draw on a larger sample of countries. Motivated by this, I run these test in the next section of this chapter.

5.2 Support groups and forests (0.5° cells)

For now, I have explored a sub-set of the data, namely democracies. However, as support coalition identity moderates the effect of democracy, it ponders the question of what the total effect of support coalition identity, regardless of regime type. This next section probes for this effect by testing **H2** - whether support groups have a non-zero effect on forest change. To do this, I re-specify the model to regress support groups directly on forest change. These specifications target average forest change when a support group is in the a regime's support coalition compared to when the group was not in the coalition. The new equation is displayed below.

$$\mathbf{ForestChange_{i,t}} = \alpha_{\mathrm{i}} + \gamma_{\mathrm{t}} + \beta_1 * SupportGroup_{\mathrm{c,t}} + \lambda * Controls_{\mathrm{i,t\text{-}1}} + \epsilon_{\mathrm{i,c,t}}$$

Here, β_1 is the coefficient for the support groups, targeting cell forest change when a particular support group is in the coalition (or dominates the coalition). Similarly to the last model α and γ represent cell and year fixed effects. λ is a vector for the control variables on the cell level at t-1. Lastly, ϵ denotes the clustered residuals values on the country and year level.

Table 5.3: Individual support group identity and global forest change (TWFE)

	Dependent variable:			
	Forest change % (t-1 to t+0)			
	(M1 Ru)	(M2 Ur)	(M3 Ae)	(M4 Be)
Rural supporters	−0.294			
	(0.263)			
Urban supporters		-0.803^{*}		
		(0.368)		
Agrarian elites (most important)			−0.299	
			(0.409)	
Business elites (most important)				$-1.163^{\dagger}$
				(0.584)
Per capita GDP (t-1)	$0.072^{\dagger}$	$0.073^{\dagger}$	$0.073^{\dagger}$	$0.069^{\dagger}$
	(0.037)	(0.037)	(0.038)	(0.037)
Δ Per capita GDP (t-1)	15.502	−0.195	15.336	9.911
	(25.317)	(15.809)	(25.308)	(22.657)
Δ Population growth (t-1)	−0.112	−0.158	−0.116	−0.120
	(0.213)	(0.184)	(0.212)	(0.204)
Forest (t-1)	-0.646^{***}	-0.649^{***}	-0.646^{***}	-0.647^{***}
	(0.044)	(0.043)	(0.044)	(0.044)
Observations	1,601,297	1,601,297	1,601,297	1,601,297
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.359	0.361	0.359	0.361
Adjusted R^2	0.338	0.339	0.338	0.339
Residual Std. Error (df = 1549605)	3.832	3.828	3.832	3.828
Note:				†p<0.1; *p<0.05; **p<0.01; ***p<0.001

For table 5.3, the first model (M1 Ru) regresses rural supporters on forest change globally, and returns null results, suggesting that rurally supported cell years on average do not have a significant effect on forest loss. Second, in model 2 (M2 Ur), the average effect of urban supporters on forest change is significant and negative (-0.803%) on the 0.05 level. For the model 3 (M3 Ae) targeting the average effect of agrarian elites on forest cover change, the effect remains insignificant. Lastly, model 4 (M4 Be), targeting forest change when urban business elites dominate the support coalition does reports back weakly significant results at the 0.1 level. In this specification, business elite supported regimes are associated with -1.163% higher than average forest loss in the period 1982 to 2015. In summary, for global forests, the pattern is different from model M1 in table 5.3, but similar to M3 SG, which is likely the effect of multicollinearity. Another notable aspect of all the models in table in 5.4 is that overall per capita GDP does yield some estimation power on grid cell forest change on the 0.1 level. These trend in a positive direction, suggestion that the larger the size of the economy, the more forest regrowth. Additionally, the lagged forest (t-1) control is highly significant, again denoting to the fact that grid cells are similar to grid cells in previous years.

Table 5.4: Individual support group identity and tropical forest change (TWFE)

	Dependent variable:			
	Forest change % (t-1 to t+0			
	(M1T Ru)	(M2T Ur)	(M3T Ae)	(M4T Be)
Rural supporters	−0.488 (0.318)			
Urban supporters		−0.694* (0.323)		
Agrarian elites (most important)			−0.442 (0.501)	
Business elites (most important)				−0.494 (0.297)
Per capita GDP (t-1)	0.042 (0.052)	0.043 (0.053)	0.044 (0.052)	0.041 (0.053)
Δ Per capita GDP (t-1)	−47.990† (27.155)	−47.695† (27.038)	−48.573† (27.111)	−48.208† (26.958)
Δ Population growth (t-1)	−0.197 (0.292)	−0.238 (0.275)	−0.195 (0.293)	−0.180 (0.284)
Forest (t-1)	−0.617*** (0.053)	−0.618*** (0.052)	−0.617*** (0.053)	−0.617*** (0.053)
Observations	559,973	559,973	559,973	559,973
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.358	0.359	0.358	0.358
Adjusted R^2	0.338	0.339	0.338	0.338
Residual Std. Error (df = 543100)	4.147	4.145	4.147	4.147
Note:		†p<0.1; *p<0.05; **p<0.01; ***p<0.001		

For tropical forests, which is addressed in table 5.4, I find a similar pattern for urban supporters (M2T Ur), which show a significant effect on forest loss (-0.694%), at the 0.05 level. However, model 4 targeting the effect of business elites (M4T Be) is not significant, unlike M2T and M2T SG in table 5.2, suggesting that these estimates also may be biased due to multicollinearity. Interestingly, unlike overall economic size which is weakly significant in the models of table 5.4, economic *growth* (Δ Per capita GDP) is a weakly significant predictor across all the models targeting tropical forest cover change.

Similarly to the interaction models in section 5.1, the models in table 5.3 and 5.4 all have a VIF score below < 2, suggesting that the assumption of no perfect multicollinearity is met. In section 5.3 I run a series of robustness tests to check the internal validity of these findings across different specifications and alternative modelling strategies (Matching).

5.2.1 Summary and interpretation of the results

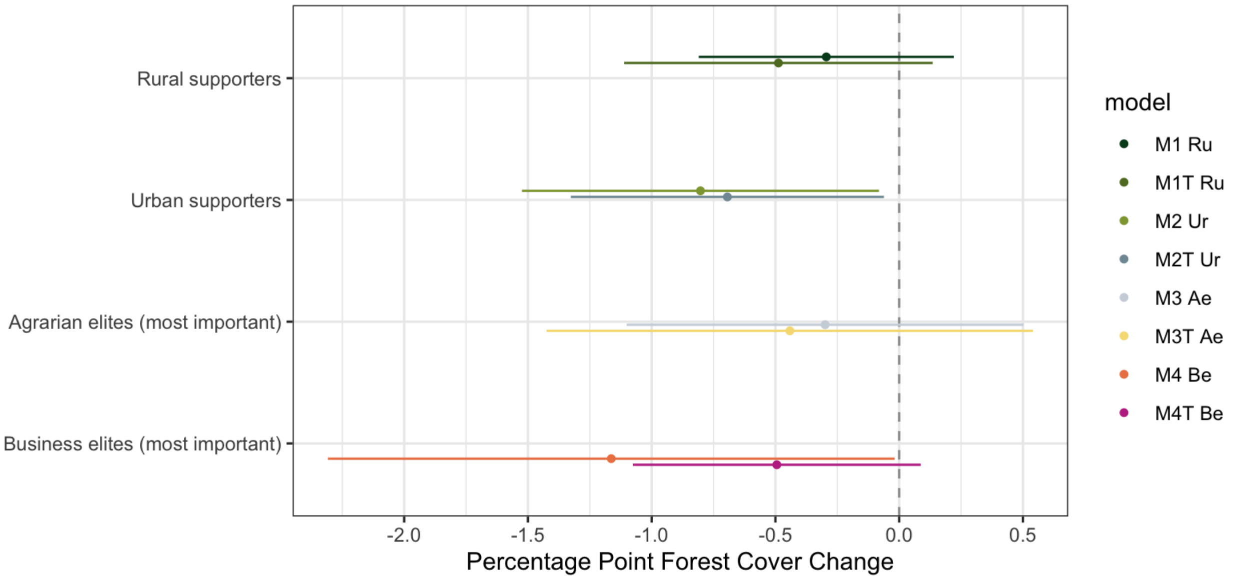


Figure 5.2: Estimated Effects of Support Groups on Forest Change

Given the assumption that the effect of support coalition identity is equal for democracies and autocracies, the above results suggests that the identity of regimes' support coalitions are significantly associated with forest cover change, and I cannot reject **H2**. In particular, I find that regimes supported by urban groups - urban working class, middle class and business elites - are associated with greater forest loss for the years 1982-2015. Hence, I argue that I find support for hypothesis *H2c*, and partial support for hypothesis *H2d*. Globally, grid cells in regimes with urban support groups, or in regimes where business elite dominate the support coalition are associated with in above-average increase in forest loss. In the tropics, I find that grid cells for regimes with urban supporters (working and middle class) also associated with on-average greater forest loss. Interestingly, these finding coincide with previous large-N studies addressing the impact of urbanization and changing consumption demands when people move to the cities (DeFires, Rudel, Uriate, et al. 2010). In light of this, the above findings suggest that these demographic and economic changes may also be reflected in *political representation*, as in when people move to the cities their material preferences also change their political preferences, which in turn affects land use and forest loss. I will elaborate more on this potential relationship in the discussion section of chapter 6. However, I did not find significant results for the rural groups (rural supporters and agrarian elites) and as such can not support hypotheses *H2a* and *H2b*.

One noteworthy limitation for the findings in section 5.1 and 5.2 is that they are contingent on the number of grid cell-years in a particular country, i.e., the larger the political unit, the more potential forest can be change. As such the validity of these findings can mostly be applied to larger countries with more forests to lose. For this reason, I run further analysis on the country-level as robustness tests in the next section.

5.3 Robustness checks

To query the robustness of the above results, I in this section I re-test some of the findings in the previous sections to a measurement of the internal validity of the results. As we do not know the true data generation process causes the observed patterns, scholars make assumptions about to model reality. This potentially opens up the door for model uncertainty, and as such robustness checks are a helpful way to control whether the results from the baseline models hold up when modifying the regressions (Lu and White 2014, p. 194). The main purpose of these checks to ensure that I have measured what I intended to measure in the models, hence giving some estimate of how valid my results are (Bryman, 2016, p. 158).

I start by checking for alternative explanations. First, whether the *location* of incumbent regimes support coalitions matters, as one could easily argue that *where* the regime supporters are located may be equally as important (if not more important) than their identity and political enfranchisement. To test the possible impact of location I run a separate specification by creating a new set of predictor dummy variables made from the "v2regsuploc" variable in the V-Dem data set (Coppedge et al. 2021).[3] The dummy variable "Ruralloc" denotes support coalitions that are primarily rurally located, while the dummy variable "Urbanloc" captures support coalitions in cities or the capital city of a country. Replicating the models in table 5.1 to 5.4, I run these models with the location variables on both the global forest data as well as the tropical sub-sample for both the moderation analysis as well as their direct effects. Both return null results, as presented in table A.1 and A.2 in appendix A. This suggests that supporter identity may be a more salient factor than where supporters are located in predicting forest cover change. I proceed by testing other alternative explanations for the observed relationships for both the interaction models and the total effect models. I check whether controlling for political corruption, executive corruption as well as log-transformed per capita GDP alters the

[3] See chapter 4.2 for an explanation of this variable.

results. As discussed in chapter 2, corruption may be a important mechanism facilitating forest loss so I add both political corruption ("v2x_corr") as well as executive corruption ("v2x_execorr") from the V-Dem data set as control variables. When including these variables, the model results remain consistent, but per capita GDP is now significant and positive on the 0.05-level and 0.01-level depending on the model specification (see table A.9, A.10, A.11 and A.12 in appendix A). This suggests that the larger the economy, the more forest regrowth across all forests, consistent with the EKC-hypothesis outlined in chapter 2. However, for the tropical forest sub-sample, tested in the interaction model in table A.12 and the total effect model in table A.10 growth in per capita GDP is negative and significant on the 0.05-level, suggesting that economic growth is associated with deforestation.

Next, I re-run the interaction models with a different measure of democracy to see if results remain consistent. Using different, but similarly defined measurements of democracy can help determine whether the results are valid across different 'thin' measurements of democracy. To do this I employ V-Dem's polyarchy measure of democracy ("v2x_polyarchy") from the Coppedge et al. 2021 data set. The model targeting global forests yields equal results as the model using the BMR measurement, with rurally supported democracies having a positive effect on forests globally, and hence being associated with reforestation, while the other interaction elements yielded null results. The main difference is that the effect size increases (3.321% forest change) for rurally supported democracies when using the V-Dem measure. The models targeting tropical forest yields null results for the interaction elements. Similarly to the previous test, these models are displayed in appendix A within table A.3 and A.4.

I continue by checking for *suppression effects*, i.e., that the estimated effect key coefficients are not a result from adding control variables. This happens when some controls increase the predictive validity of another variable (or set) by its inclusion in the regression equation through opaque mechanisms (Lenz and Sahn 2020, p. 356-7). For this reason, I remove the key economic and demographic control variables: Per capita GDP, Δ Per capita GDP and Δ Population growth. For the interaction models, I find that the the results remain consistent across global and tropical forests, however the estimated positive of effect size of democracy moderated by rural supporters (democracy * rural supporters) *increases* to 2.499% and significant at the 0.01 level (see table A.5 and A.6). Similarly for the models targeting the effect of support groups directly on forest cover change, I find that the main results (urban supporters having a significant effect on forest cover change at the 0.05 level, and business elites having a significant effect on forest cover at the 0.01 level) remain consistent (see table A.7 and A.8). Interestingly, when removing controls, rural support groups have a significant total effect on forest change at the 0.05 level. I argue that both the increased effect size of rural supporters in the interaction model as well the significant effects in the models regressing the groups directly on forest change are a result of omitted variable bias, meaning if I did not include additional control variables I would have over-estimated the effect of rural support groups on forest change by not including relevant variables.

Given that the overall results from the above robustness checks remain quite consistent across various model alterations, I argue that the results for the cell year data set are internally valid and that I have measured what I intended to measure. However, as the main results are statistically significant at the 0.05-level, that means that there is still a 5% chance of making type-I error, meaning that I can only say that these results are somewhat robust.

5.3.1 Country Level Analysis: Mahalanobis Distance Matching

A different question, however, is whether the results are consistent across different levels of aggregation. For that reason, the next set of robustness checks I use the country-aggregated data, essentially questioning whether the above estimates hold for smaller political units, or whether the effect is driven by large countries. As mentioned in chapter 4, in this data set the geographic size of each country is not taken into consideration, i.e., percentage point forest change is weighted equally for Brazil as well as Denmark. This measure has been made by taking the average forest change rate of all the grid cells in one country for one year. In this way, if significant results are found, that gives further validity to the association being similarly pronounced across small countries as well as large countries.

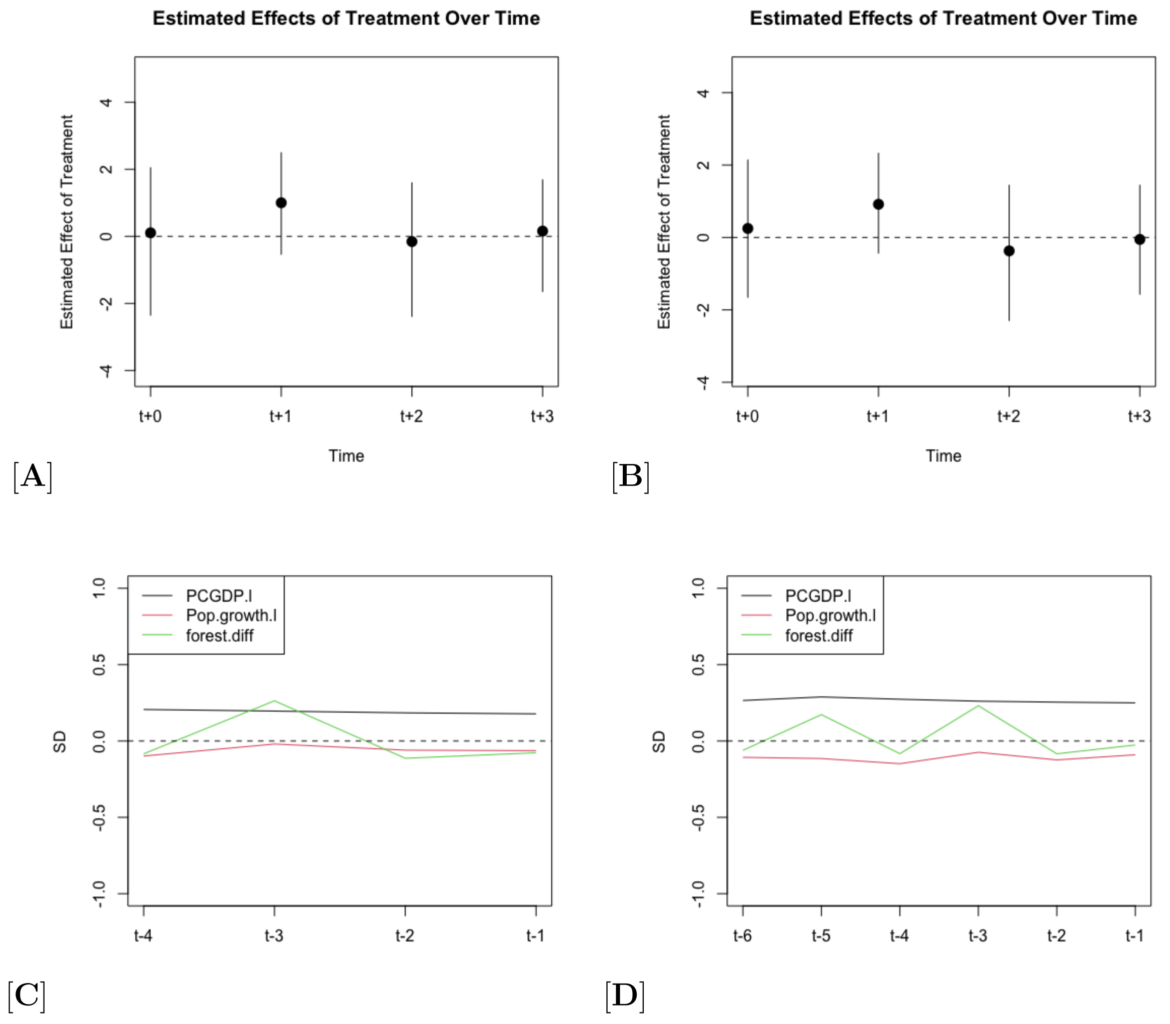
As one of the main findings in the previous section is that regimes supported by urban supporters as well as by business elites are associated with higher-than-average forest loss, I re-test this using Mahalanobis distance panel matching on the country-aggregated data set. I also include TWFE models with country aggregated data in appendix A.[4] However, Imai and Kim (2021) point out, TWFE model assumes additive linear effects, and it is impossible to simultaneously adjust for unobserved unit-specific and time-specific confounders. In this regard, panel matching provides more precise estimates as it specifies counterfactuals and gives an assessment of matching quality. The models below target a different relationship than in the FE models, namely testing the sequential effects of support groups *entering* the support coalition. Essentially, this test is asking the question: "What happens to forest change when urban supporters or business elites enter the support coalition?"

In figure 5.2, I have displayed the panel matching analysis targeting effect of urban supporters on forest change. Here, the dot-and-whiskers in sub-figure **A** represents the estimated average treatment effect on the treated (ATT) in percentage points, meaning the average estimated effect on forest cover change for those countries where urban supporters enter the regime's support coalition. Sub-figure **A** shows the ATT for matched countries with 3-year pre-treatment matching periods, meaning the instructed treatment history that the 'panelmatch' algorithm searches for to create a matched data set. Treated and control units are matched on whether or not they have similar matching treatment histories based on their lagged per capita GDP and Δ Population growth. I limit matching to these two controls as adding additional variables would prune away more units, limiting statistical power and heightening the covariate balance of the two matched data sets. The first matching model displayed in **A** returns null results with a 95% confidence interval after the 10 best matches are given equal weight in the model (matched set, $N =$

[4] As seen in table A.9, these return null results, suggesting that the TWFE results are driven by large countries.

53 countries).[5] Similarly, the model in sub-figure **B** with a longer 5-year pre-treatment matching period also returns null results with a 90% confidence interval after the 10 best matches are given equal weight (matched set, $N = 53$ countries). Sub-figure **C** & **D** both denote the above models covariate balance, suggesting the model in sub-figure **A** has better overall covariate balance, but utilizes less information on pre-treatment history. Both estimates have been bootstrapped 1000 times, improving the estimates of the standard errors (the ATT and standard errors for the time periods are displayed in appendix C).

Figure 5.3: Urban Supporters as Treatment: 3- and 5-Year Pre-Treatment Match.



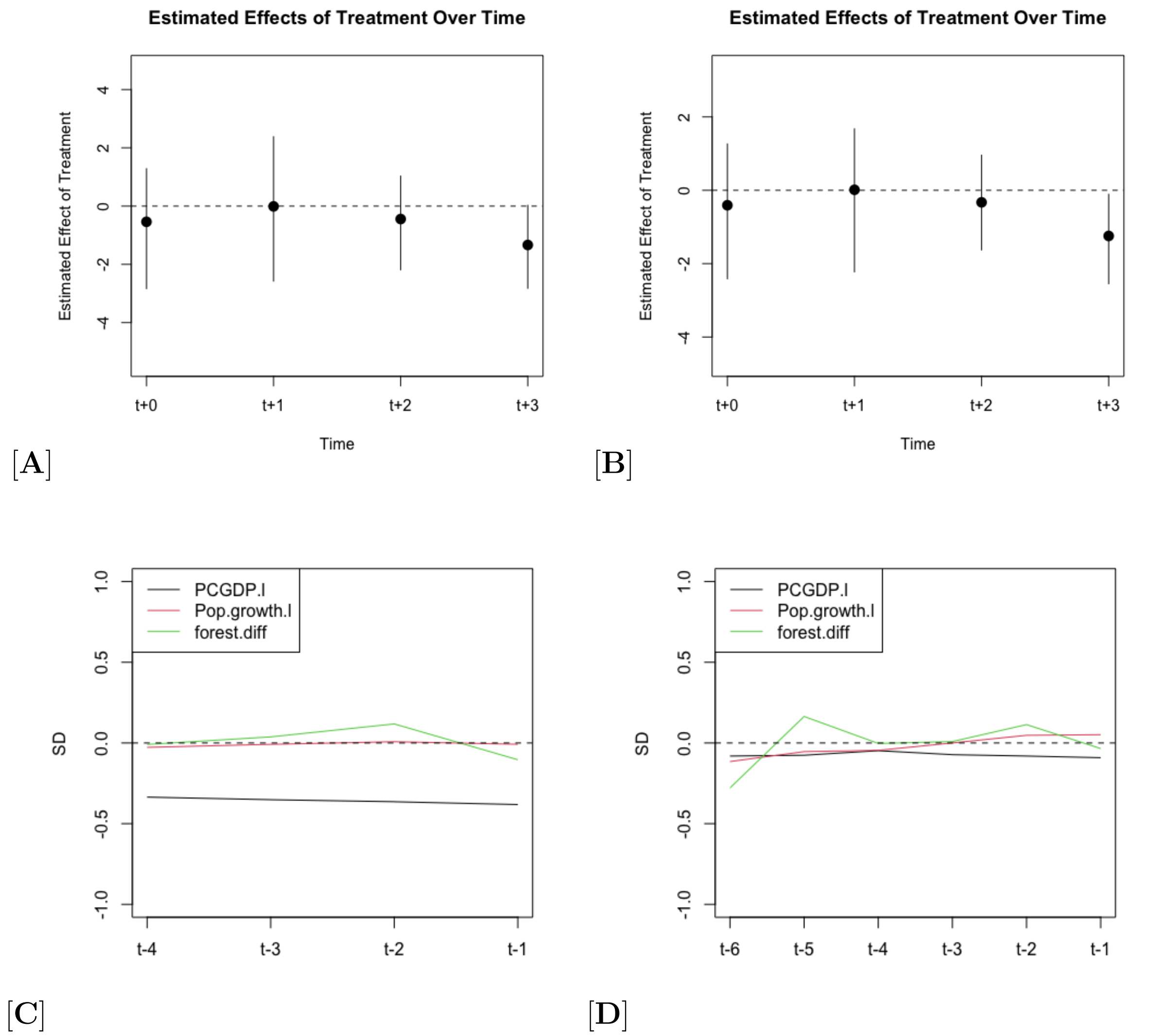
(A) Forest change: Matching w/3-year pre-treatment, (B) Covariate balance, 3-year pre-treatment, (C) Forest change: Matching w/5-year pre-treatment, (D) Covariate balance, 5-year pre-treatment.

Moving on to figure 5.3, the panel matching analysis for targeting the effect of business elites on forest change. Sub-figure **A** shows the ATT when business elites enter and dominate (as the most important group) the support coalition with 3-year pre-treatment match and 95% confidence interval (matched set, $N = 43$ countries). This shows a non-significant effect. However, addressing the covariate balance of this matched data

[5] The countries in the matched data set include both the treated countries and the control countries.

set shown in sub-figure **C** suggests that further optimization of the matched set can improve estimates. The model shown in sub-figure **B** has a better overall covariate balance (shown in **D**, being closer to 1 standard deviation from one another) and 5-year pre-treatment history match shows that there is a significant negative effect at t+3 (-0.109 to -2.546% forest loss), however with a 90% confidence interval (matched set, $N = 44$ countries). Similarly as for the previous figure, the estimated ATT and standard errors for the different time periods can be found in appendix C.

Figure 5.4: Business Elites as Treatment: 3- and 5-Year Pre-Treatment Match.



(A) Forest change: Matching w/3-year pre-treatment, (B) Covariate balance, 3-year pre-treatment, (C) Forest change: Matching w/5-year pre-treatment, (D) Covariate balance, 5-year pre-treatment.

Ultimately, these findings give less confidence in the notion that the effect urban supporters are equally pronounced in smaller countries, suggesting that the effects found in section 5.2 is driven by larger countries with much forest. For business elites, a 'similar' estimate as for the previous section is found, with the effect of business elites on forest cover change only being significant at the 0.1 level, suggesting that the effect of business elites is similar for both larger and smaller countries (table B.4 in appendix B gives some intuition of which regimes were associated with higher levels of deforestation). The matching analysis also suggests that there could be a *sequential* effect when business elites enter a regime's support coalition in which deforestation peaks a few years after these groups enter the coalition. I will further elaborate on this possibility in chapter 6.

5.4 Validity and Limitations

Given the results in the previous sections, I have argued that the results for the cell-level results remain relatively valid across various model specification, with the main caveat being that the effect of urban supporters is not pronounced on the country-aggregated data. However, I underscore that these results are not evidence of a causal relationship. While the overall goal of any theoretical test is to test the strength of a potential causal relationship, it is difficult to account for omitted variable bias when studying relationships on a global level. While including entity- and time fixed effects or employing quasi-experimental panel matching designs does theoretically account for this effect, the vast heterogeneity among the studied countries makes it very difficult to determine causal estimates. Yet, the purpose of this thesis has been to probe for viable *associations* that are in line with theorized expectations, which in turn can be investigated causally.

While I argue that my findings are valid, they come with limitations. Acknowledging limitations is important as it helps place the research in context and shed light on systematic bias that the scholar did not or could not control for, which could have inappropriately affect the results (Ioannidis 2007, p. 324). First, it is worth noting one obvious limitation which is that the dependent variable (forest cover change) and the independent variable/interaction/control variables (democracy, support groups and controls) are on different levels of aggregation, on the cell and country-levels. This can create measurement error as measurements on the country-level are aggregated down to the cell level as there is no spatial data on levels of democracy on the 0.5° grid cell level, nor data capturing regime support groups on the 0.5° grid cell level. Yet, I have argued that spatial detail is valuable as cell level data is closer to the *actual* level of treatment, as a theorized national level change in regime (through democratization, or the introduction of a new support group) has local or provincial deforestation consequences. Additionally, it is uncertain whether more spatially detailed data on the independent variable would have been the appropriate data for testing the theoretical proposition in this thesis, which focuses on the moderating effect/total effect of political enfranchised support groups, which does not necessarily need to be linked to the direct geographic footprint of the supporters. While I have addressed support coalition identities based on certain socioeconomic identities (such as class), there is also the possibility that other identity indicators have predictive power such as ethnic identities (e.g. Wucherpfennig, Weidmann, Girardin, et al. 2011).

Second, the number of observations for the support group variables are limited (in number of years), which creates less variation to draw inferences from, potentially biasing the estimates and inflating standard errors. As such, the data may be insufficient to detect significant associations between the independent variables and the outcome causing Type-II errors, that is, the failure to reject a null hypothesis that is actually false. Partially, the lack of active observations is due to the relatively limited time-frame from 1982 to 2016, but also due to the relatively even number of rural and urban support groups across this time-frame. This especially limits the test of hypothesis 1 (**H1**), testing the interaction effects of support groups on democracy, as there is a limited number of years where democratic transitions (61) and support groups overlap.

Another potential issue is that the support group variables themselves are categorical and aggregated from expert coded data, which further increases uncertainty and limits the information that they can provide. Ideally, directly observable data on a regime's supporters would be preferable (e.g. members of the cabinet, or the ruling political parities within a country), as one would avoid potential issues related to expert disagreement on coding decisions, as well as increase tractability of the measured concept - showing exactly what, for instance, rural supporters look like in a country in a given year. However, this problem can possibly be mitigated in future studies which have access to more precise data.

Third, a technical limitation is that the size of the forest cover data set limits the number of statistical software packages that can be used with it, the 'lfe'-package for R being one of the exceptions due to its ability to specify fixed effect models with large panel data. Given that the distribution of the dependent variable shows signs of being heavy-tailed (see appendix C), specifying similar regressions with weighted least squares may have improved estimates for the observations in the 'tails' of the distribution, yet 'lfe' does not allow for negative weights. Similarly, it would have been interesting to employ the 'panelmatch' package on the cell-level data, but this was not possible due the number of observations and needed computational power. Another possibility would be to probe for spatial heterogeneity using geographically weighted regressions. These problems and other modelling techniques may also be addressed in future studies.

Fourth, while the results in this chapter have been interpreted in light of the underlying assumption that varying social identity of a support coalition can affect levels of forest loss differently, there are many possible explanations for the pattern seen in this thesis. As explored in the literature review in chapter 2, deforestation is a complex phenomena, and any 'catch-all' explanation of global forest change should be regarded with scepticism. Economic and demographic drivers are likely part of the mix (as previous studies have established), and I find evidence for this on the cell level in table 5.4 and 5.5, where the overall size of a country's economy and its economic growth also has a significant effect on forest cover change. Robustness tests using the natural logarithm of per capita GDP also reveal that the size of a country's economy, as well as economic growth has a statistically significant impact on forest change (see table A.9, A.10, A.11 and A.12 in appendix A).

Lastly, an important limitation to consider is that the causes of forest change is likely temporal in nature, and thus varies over time and space. This thesis covers the period of 1982 to 2016, making it difficult to argue for long-term external validity. The next decades may see rapid changes in the structure of the global political economy as countries need to transition towards more sustainability. This *may* alter future forestation patterns, rendering the results in this thesis temporally invalid. Despite these limitations, I argue that this thesis constitutes one of few systematic attempts to explore the different effects of political support bases on forest cover change and how it interacts with regime type. This may have theoretical implications for other environmental indicators given the variety of interest that these groups have.

Chapter 6

Discussion and Conclusion

Does the identity of a regime's supporters moderate the effect of democracy on deforestation? The results in chapter 5 suggests that yes, between 1982 and 2016 different support coalitions are associated with variation in democratizing countries' forest change outcomes. Notably, the presence of rural groups in the regime's support coalition under democracy is associated with reforestation (more forests). Additionally I have probed for the total effect of support coalition identity on forest cover change, this thesis has argued that incumbent regimes supported by urban groups are significantly associated with higher-than-average forest loss, both across forests globally as well for tropical forests which have a particularly important effect in mitigating global climate change. In this chapter, I discuss my main findings in detail, how it relates to theoretical expectations as well as suggest avenues for further research.

6.1 Main Findings and Implications

First, encouragingly, I find that when a country transitions to democracy with rural groups in the support coalition, that transition is associated with *increases* in forest cover, supporting the expectations in hypothesis *H1a*. This could indicate that in regimes where these groups are included in the regime's support coalition and empowered by democracy, forest management improves, as suggested by Klooster and Masera (2000). When interacting democracy with the other support groups - urban supporters, agrarian elites and business elites, democracy does not have significant effect on forest cover change. The second test, targeting the interaction between the support groups and democracy on the tropical forests sub-sample also returns null results. Interestingly, democracy regressed directly on the tropical forest sub-sample is also not statistically significant (as seen in model M1T, table 5.2). Both of these findings are surprising given that the case-study literature on democracy and deforestation often focuses on countries in the 'tropical belt' (such as Indonesia, Brazil, Colombia etc.). My findings imply that the average effect of democratic rule is not associated with increased forest loss across tropical forests.

Given this, I argue that while the overall total forest loss among democratizing countries since 1982 has been higher under democracy than under autocracy (as pointed out by Sanford 2021), there is much variation between democratizing countries depending on individual regime's characteristics. As such I argue that I find support for hypothesis **H1** - that the effect of democracy on forest cover change is moderated by the identity of the regimes' support coalition. This argument comes with limitations, such as the sample size of democratizing countries (61) contingent on the temporal limitations of the Song, Hansen, Stehman, et al. (2018) data set.

These result also raise the question of whether utilizing a 'thin' definition of democracy (such as the BMR measure used in this thesis) is analytically productive for investigating environmental change, such as degradation of forests. One potential avenue for furthering the understanding of how democracy affects forests change would be to employ a set of 'thicker' definitions of democracy, such as the different V-Dem measures of democracy. As democracy can be considered a multidimensional phenomenon (Coppedge 2012), varieties of democracy may yield different insights into forest cover change.

I also find support for my second hypothesis (**H2**) suggesting that support coalition identity has a non-zero effect on forest cover change. Particularly, I find that the urban groups are associated with higher-than-average forest cover loss when entering the support coalition. While this pattern may at first seem counter-intuitive from the assumption that rural groups are thought to have a more acute need to utilize forests where forests where they are *actually* located, it appears to reflect the larger political and economic implications of global urbanization to cities that the last three decades have seen. Indeed, my second findings seem to overlap with the observations of DeFries, Rudel, Uriate and Hansen (2010), who point out that urban population growth - not rural population growth - is associated with higher levels of tropical forest loss. They argue that urbanization raises consumption levels and demand for agricultural products and land use. Additionally, they point out that forested landscapes that are stabilizing or depopulating might actually exacerbate deforestation, as these depopulated areas can be used for satisfying demands by urbanizing populations (DeFries, Rudel, Uriate, et al. 2010, p. 180). In light of this, my findings suggests that migration to the cities and urban areas may in turn empower urban politicians to facilitate the rising consumption demands of urban groups, which results growing land utilization, and by proxy, deforestation.

These observations raise the question of whether urban supporters are, or have become more detached from nature? There is a puzzle here, as extant evidence suggests that people living in urban areas and cities hold *more* environmentally conscious attitudes (e.g. Liu and Mu 2016). One possible explanation is that the causal chain from individuals' environmental consciousness to effective environmental legislation is long, and it is likely that other intervening factors may 'dilute' urban groups willingness to participate and enact sufficient environmental policy, such as opportunities for political contestation and inclusion contingent on regime type. Yet, understanding changing preferences towards the environment as a result of migration from rural to urban areas, and importantly, individual willingness to promote environmental sustainability in different institutional environments are potential avenues for further research.

The third finding in this thesis, highlighted by the partial support for *H2d*, suggests that in regimes where urban business elites dominate the incumbent regime's support coalition are also associated with higher-than-average forest loss. One interesting finding from the robustness checks suggests that that these groups could have a sequential effect on forest change, i.e. after these elites become the regime's most important support group, something that changes that might cause more deforestation. In light of theory, this might be for different reasons than for urban supporters (urban working- and middle class, and labour unions). In chapter 3, I synthesized observations from case studies and suggested that when these groups are in the support coalition of an incumbent regime, these groups have an interest in engaging in rent-seeking activities that lessens environmental protections that could have an adverse effect on forests. However, this effect is weaker than for urban groups, given that the risk of type-I error is greater than 5%. Given the weak effects found (although consistent across levels of aggregation), as well as the limited sample size, more in-depth exploration and data collection on cases is needed to further validate this hypothesis. Future studies may benefit from a mixed methods approach, identifying countries where business elites play a prominent role in politics and combine spatial data on forest change with detailed case-based knowledge. Another interesting iteration of this question would be to address the distributional trade-off between environmental degradation and economic development, to address which groups benefit from environmental degradation such as deforestation. In this regard, future studies can include variables covering economic equity in their analysis of environmental degradation.

Lastly, while this thesis addressed the effect of democracy on forest cover change, another potentially salient characteristic of democratic rule is *election cycles*, which are predicted to amplify the relative political value of forests for incumbent politicians as a distributive good (Sanford 2021). A possible avenue for further research could be to adopt a similar theoretical framework used in this thesis to investigate whether different political support bases have an effect on forest cover change during electoral cycles.

6.2 Concluding Remarks

Extensive research has been done into the effects of political institutions on environmental degradation, with a particular emphasis on the effects of democracy. In this thesis, I have argued that we need a more nuanced understanding of these processes and suggested that disaggregating the composition of individual regime's support coalitions can reveal additional insights into democracy's effect on forest cover change, an important environmental indicator given the role forests have in mitigating global climate change. My main argument has been that different support coalitions may have different economic and political interests in society which in turn could affect rates of deforestation. To study this, I leveraged two data sets - satellite measurements of forest cover aggregated into 0.5° grid cell panel data from 1982 to 2016 by Song, Hansen, Stehman et al. (2018), and V-Dem data measuring the identity of individual regime's support coalitions by Coppedge, Gerring, Knutsen, et al. (2021). I have uncovered some interesting correlations that can be interpreted in light of theory; however these cannot give a causal explanation of the observed change in forests. This requires further in depth enquiry.

Given this, I have argued that the identity of a regime's support coalition moderates the deforesting effect of democracy on global forests, as found by Sanford (2021). I find that that democracy interacted with a rural support coalition is associated with an on average *increase* in forest cover between 1982 and 2016 (+1.713%), which can imply that the inclusion of rural groups in a democratizing country's support coalition improves forest management (as suggested by Klooster and Masera 2000). When interacting the other support groups with democracy, these return statistically insignificant result. Moreover, running the same tests on the reduced tropical forest sample, I find that neither democracy, nor democracy interacted with different support groups has a significant effect on forest change. As such, I also argued that the effect of democracy on forest change varies different forest types. For further research, I recommend that future studies addressing the effects of democracy on forests may benefit for looking at a variety of democracy indicators, such as the different V-Dem indicators.

Motivated by the findings from the moderation analysis, I have probed for the total effect that different support coalitions have on forest cover change, regardless of regime type. The findings from this analysis imply that when urban supporters (working- and middle class) are present in the support coalition, deforestation on average increases across global forests (-0.803%), as well as for the sub-sample of tropical forests (-0.694%). The associated loss in tropical forest cover is particularly alarming, given the unique role that these biomes have in managing the Earth's climate. In light of DeFries, Rudel, Uriate, et al. (2010), I argue that this implies that migration to the cities and urban areas may in turn empower urban politicians to facilitate the rising consumption demands of urban groups, which results growing land utilization, and by proxy, deforestation. Lastly, I also find some weak evidence for urban business elites being associated with higher-than-average forest loss when they dominate the incumbent regime's support coalition. This also requires further enquiry to validated, yet remains consistent across different levels of aggregation.

As the UN's *World Urbanization Prospects* estimates that by 2050 about 70% of the world's population will live in cities or urban areas, it heralds an enormous transformation that will change the lives for billions of people (UN 2018). Migration into cities and urban areas will change people's material needs, altering political interests along the way. Could a more urban world empower politicians that exacerbate environmental degradation in the form of deforestation, despite citizens growing environmental awareness as they move to cities? I have attempted to highlight this puzzle in my discussion and argued that it validates further inquiry into individual-level political preferences as people migrate from rural to urban areas.

Furthering our understanding of the political drivers of deforestation is of upmost importance given the role intact forests have in mitigating global climate change, providing ecosystem services, flood and drought mitigation as well as improved air quality. In thesis, I have argued that studying the characteristics of individual regime's support coalitions can yield insights into the incentives that different groups have to deforest. This may have implications for other environmental indicators as well, and I therefore encourage others to use this approach.

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Appendix A

Robustness Checks

Support Coalition Location Instead of Coalition Identity

In this models, I test the possibility of different support coalitions geographical location being a more relevant predictor that support group using a set dummy variables made from the the "v2regsuploc" variable in the V-Dem data set. The dummy variable "Ruralloc" denotes support coalitions that are primarily rurally located, while the dummy varibale "Urbanloc" captures support coalitions in cities or the capital city of a country. These models return null results. The regressions in table A1 targets the effect of support coalitions location directly on forest change (global and tropical). Table A2 looks at the marginal effects of democracy depending on different support coalitions location (global and tropical).

Table A.1: Support Coaltion Location and Forest change

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Rural location	−0.422		−0.238	
	(0.421)		(0.563)	
Urban location		−0.171		−0.184
		(0.133)		(0.151)
Per capita GDP (t-1)	0.073*	0.072*	0.044	0.043
	(0.037)	(0.037)	(0.053)	(0.052)
Δ Per capita GDP (t-1)	15.518	15.199	−48.432*	−48.825*
	(25.414)	(25.309)	(27.042)	(27.147)
Δ Population growth (t-1)	−0.138	−0.118	−0.220	−0.200
	(0.213)	(0.211)	(0.309)	(0.292)
Forest (t-1)	−0.646***	−0.646***	−0.616***	−0.617***
	(0.044)	(0.044)	(0.053)	(0.053)
Observations	1,601,297	1,601,297	559,973	559,973
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.359	0.359	0.358	0.358
Adjusted R^2	0.338	0.338	0.338	0.338
Residual Std. Error	3.832 (df = 1549605)	3.832 (df = 1549605)	4.147 (df = 543100)	4.147 (df = 543100)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.2: Interaction Models: Democracy and Support Coalition Location

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Democracy (BMR)	-1.163^{***}	-1.025^{**}	-0.527^{*}	-0.304
	(0.392)	(0.410)	(0.287)	(0.379)
Rural location	-1.144		-0.629	
	(0.754)		(0.826)	
Democracy x Rural location	1.141		0.808	
	(0.860)		(0.857)	
Urban location		-0.050		0.047
		(0.107)		(0.195)
Democracy x Urban location		-0.117		-0.335
		(0.136)		(0.208)
Per capita GDP (t-1)	0.064^{*}	0.060	0.033	0.032
	(0.037)	(0.037)	(0.054)	(0.053)
Δ Per capita GDP (t-1)	-5.043	-4.272	-46.330^{*}	-48.083^{*}
	(15.383)	(15.504)	(26.539)	(27.152)
Δ Population growth (t-1)	-0.169	-0.130	-0.217	-0.191
	(0.188)	(0.190)	(0.315)	(0.301)
Forest (t-1)	-0.655^{***}	-0.655^{***}	-0.625^{***}	-0.625^{***}
	(0.043)	(0.043)	(0.052)	(0.058)
Observations	1,545,318	1,545,318	542,137	542,137
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.366	0.365	0.363	0.362
Adjusted R^2	0.344	0.343	0.342	0.342
Residual Std. Error	3.842 (df = 1493733)	3.844 (df = 1493733)	4.167 (df = 525268)	4.168 (df = 525268)
Note:				*p<0.1; **p<0.05; ***p<0.01

Alternative Measure of Democracy for Interaction Models

In this part, I use V-Dem's Polyarchy index instead of the BMR measurement to see if it yields similar results for the interaction models. For global forests, depicted in table A.3, the beta coefficient for Polyarchy moderated for rural support groups (model 1) displays similar results as for the BMR model in chapter 5. Also similarly, the model targeting the sub-sample of tropical forests returns null results for the interaction elements (table A.4).

Table A.3: Interaction Models: Polyarchy (V-Dem), support groups and global forests

	Dependent variable:				
	forest.diff				
	(1)	(2)	(3)	(4)	(5)
Polyarchy (V-Dem)	−3.166*	−3.631*	−2.137	−3.379*	−3.150*
	(1.292)	(1.378)	(1.185)	(1.361)	(1.292)
Rural supporters		−1.877*			
		(0.790)			
Polyarchy x Rural supporters		3.321*			
		(1.459)			
Urban supporters			0.166		
			(1.016)		
Polyarchy x Urban supporters			−1.204		
			(1.852)		
Business elites				−2.269*	
				(1.077)	
Polyarchy x Business elites				2.380	
				(1.474)	
Agrarian elites					0.645
					(0.868)
Polyarchy x Agrarian elites					−1.211
					(1.238)
Per capita GDP (t-1)	0.045	0.042	0.050	0.045	0.045
	(0.034)	(0.033)	(0.036)	(0.034)	(0.034)
Δ Per capita GDP (t-1)	6.399	4.057	1.826	0.430	6.457
	(16.961)	(16.343)	(14.340)	(15.183)	(16.980)
Δ Population growth (t-1)	−0.167	−0.129	−0.189	−0.189	−0.165
	(0.181)	(0.188)	(0.163)	(0.174)	(0.181)
Forest (t-1)	−0.648***	−0.650***	−0.649***	−0.649***	−0.648***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Observations	1,597,247	1,597,247	1,597,247	1,597,247	1,597,247
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes	
R^2	0.362	0.363	0.363	0.363	0.362
Adjusted R^2	0.341	0.342	0.341	0.342	0.341
Residual Std. Error	3.809 (df = 1545560)	3.807 (df = 1545558)	3.808 (df = 1545558)	3.805 (df = 1545558)	3.809 (df = 1545558)
Note:					*p<0.05; **p<0.01; ***p<0.001

Table A.4: Interaction Models: Polyarchy (V-Dem), support groups and tropical forests

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Polyarchy (V-Dem)	−2.392*	−1.138	−2.360*	−2.225*
	(1.403)	(1.076)	(1.351)	(1.245)
Rural supporters	−1.231			
	(0.950)			
Polyarchy x Rural supporters	1.874			
	(1.641)			
Urban supporters		0.659		
		(0.831)		
Polyarchy x Urban supporters		−2.070		
		(1.674)		
Business elites (most important)			−0.692	
			(0.726)	
Polyarchy x Business elites			0.761	
			(1.375)	
Agrarian elites (most important)				0.502
				(1.053)
Polyarchy x Agrarian elites				−1.148
				(1.324)
Per capita GDP (t-1)	0.016	0.026	0.015	0.017
	(0.055)	(0.054)	(0.055)	(0.054)
Δ Per capita GDP (t-1)	−42.426*	−42.216*	−41.593*	−41.612*
	(22.064)	(22.511)	(22.354)	(22.302)
Δ Population growth (t-1)	−0.088	−0.206	−0.118	−0.114
	(0.273)	(0.228)	(0.265)	(0.267)
Forest (t-1)	−0.617***	−0.618***	−0.616***	−0.616***
	(0.050)	(0.050)	(0.050)	(0.050)
Observations	556,841	556,841	556,841	556,841
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.359	0.359	0.359	0.359
Adjusted R^2	0.339	0.339	0.339	0.338
Residual Std. Error (df = 539971)	4.106	4.104	4.106	4.107
Note:				*p<0.1; **p<0.05; ***p<0.01

Suppression effects: Removing Economic and Demographic Control Variables

For this robustness test I remove the key control variables, namely per capita GDP (t-1), delta per capita GDP (t-1) and delta population growth (t-1). Similarly to the previous robustness tests, I first test the interaction models (table A.5 and A.6). The results in these models are consistent with the results of the baseline models in chapter 5, one notable aspect here is that removing controls causes business elites to become significant at the 0.1 level. Second, I check whether the models targeting the effect of regime support groups directly on forest change without controls yield similar results as the models with controls (table A.7 and A.8), although now rural supporters (in A.7) also return significant results. As discussed in chapter 5 section 5.3, I argue that this is the result of omitted variable bias.

Table A.5: Interaction Models: Democracy and support groups (global, no controls)

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Democracy (BMR)	−1.108***	−0.699*	−0.740**	−0.747**
	(0.375)	(0.349)	(0.335)	(0.312)
Rural supporters	−1.879***			
	(0.383)			
Democracy x Rural supporters	2.499***			
	(0.649)			
Urban supporters		−1.189**		
		(0.447)		
Democracy x Urban supporters		0.692		
		(0.488)		
Agrarian elites (most important)			1.564	
			(1.260)	
Democracy x Agrarian elites			−1.465	
			(1.260)	
Business elites (most important)				−1.557**
				(0.651)
Democracy x Business elites				0.772
				(0.602)
Forest (t-1)	−0.645***	−0.643***	−0.637***	−0.637***
	(0.041)	(0.040)	(0.041)	(0.041)
Observations	1,660,682	1,660,682	1,660,682	1,660,682
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.360	0.358	0.355	0.356
Adjusted R^2	0.339	0.337	0.334	0.335
Residual Std. Error (df = 1608639)	3.863	3.871	3.879	3.876
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.6: Interaction Models: Democracy and support groups (tropical, no controls)

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Democracy (BMR)	−0.521	−0.410	−0.421	−0.653
	(0.394)	(0.328)	(0.340)	(0.424)
Rural supporters	-1.168^{*}			
	(0.580)			
Democracy x Rural supporters	0.868			
	(0.687)			
Urban supporters		-0.846^{*}		
		(0.484)		
Democracy x Urban supporters		0.331		
		(0.577)		
Agrarian elites (most important)			1.236	
			(1.712)	
Democracy x Agrarian elites			−1.896	
			(1.600)	
Business elites (most important)				-1.544^{**}
				(0.676)
Democracy x Business elites				1.219^{*}
				(0.663)
Forest (t-1)	-0.623^{***}	-0.624^{***}	-0.623^{***}	-0.624^{***}
	(0.052)	(0.052)	(0.052)	(0.052)
Observations	553,644	553,644	553,644	553,644
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.360	0.360	0.359	0.360
Adjusted R^2	0.339	0.339	0.339	0.340
Residual Std. Error (df = 536446)	4.155	4.154	4.155	4.153
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.7: Support groups and forest change (global, no controls)

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Rural supporters	-0.941^{**}			
	(0.416)			
Urban supporters		-0.971^{**}		
		(0.379)		
Agrarian elites (most important)			0.281	
			(0.305)	
Business elites (most important)				-1.030^{*}
				(0.545)
Forest (t-1)	-0.629^{***}	-0.631^{***}	-0.626^{***}	-0.627^{***}
	(0.042)	(0.041)	(0.041)	(0.041)
Observations	1,740,277	1,740,277	1,740,277	1,740,277
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.350	0.351	0.348	0.349
Adjusted R^2	0.330	0.331	0.328	0.329
Residual Std. Error (df = 1688093)	3.855	3.851	3.860	3.857
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.8: Support groups and forest change (tropical, no control)

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Rural supporters	−0.527			
	(0.314)			
Urban supporters		−0.719**		
		(0.349)		
Agrarian elites (most important)			−0.406	
			(0.455)	
Business elites (most important)				−0.582
				(0.386)
Forest (t-1)	−0.613***	−0.615***	−0.613***	−0.613***
	(0.053)	(0.052)	(0.053)	(0.053)
Observations	579,124	579,124	579,124	579,124
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.354	0.355	0.354	0.354
Adjusted R^2	0.334	0.335	0.334	0.334
Residual Std. Error (df = 561889)	4.123	4.121	4.124	4.123
Note:				*p<0.1; **p<0.05; ***p<0.01

Natural logarithm of per capita GDP and V-Dem Corruption Indicies

In this test, I check whether the natural logarithm of GDP, as well as different types of corruption (political corruption and executive corruption) affects the results. The corruption variables are sourced from the V-Dem data set, denoted as "v2x_corr" and "v2x_pubcorr". In brief, using the natural logarithm of per capita GDP shows how economic factors can both increase forest cover (in line with the EKC hypothesis outlined in chapter 2), as well decrease forest cover through growth rates.

Table A.9: Log-PCGDP, corruption and global forests

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Rural supporters	−0.448			
	(0.336)			
Urban supporters		−0.879***		
		(0.282)		
Agrarian elites (most important)			0.187	
			(0.220)	
Business elites (most important)				−1.190*
				(0.590)
Ln per capita GDP (t-1)	0.970***	0.938***	0.966***	0.995***
	(0.275)	(0.271)	(0.273)	(0.289)
Δ Per capita GDP (t-1)	8.164	−8.386	7.709	2.037
	(25.774)	(16.009)	(25.715)	(22.481)
Δ Population growth (t-1)	0.076	0.034	0.061	0.054
	(0.229)	(0.195)	(0.226)	(0.220)
Political corruption (V-dem) (t-1)	0.338	−0.462	0.504	0.787
	(3.388)	(3.126)	(3.366)	(3.382)
Executive corruption (V-dem) (t-1)	−2.233	−1.951	−2.241	−2.105
	(2.020)	(1.783)	(2.013)	(1.956)
Forest (t-1)	−0.651***	−0.653***	−0.651***	−0.651***
	(0.044)	(0.044)	(0.044)	(0.044)
Observations	1,594,842	1,594,842	1,594,842	1,594,842
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.361	0.363	0.361	0.363
Adjusted R^2	0.340	0.342	0.340	0.341
Residual Std. Error (df = 1543163)	3.834	3.829	3.834	3.829
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.10: Log-PCGDP, corruption and tropical forests

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Ruralsup	−0.503			
	(0.339)			
Urbansup		−0.543**		
		(0.221)		
Agrelite_mimp			0.213	
			(0.303)	
Busielite_mimp				−0.664*
				(0.366)
Ln Per capita GDP (t-1)	1.168**	1.140**	1.165**	1.167**
	(0.514)	(0.509)	(0.513)	(0.497)
Δ Per capita GDP (t-1)	−53.258**	−53.058**	−54.345**	−53.609**
	(25.044)	(25.165)	(25.035)	(24.764)
Δ Population growth (t-1)	−0.187	−0.213	−0.203	−0.175
	(0.207)	(0.208)	(0.209)	(0.189)
Political corruption (V-dem) (t-1)	4.193	3.895	4.430	4.470
	(2.991)	(2.748)	(2.938)	(2.945)
Executive corruption (V-dem) (t-1)	−2.216	−2.098	−2.252	−2.086
	(1.793)	(1.668)	(1.751)	(1.780)
Forest (t-1)	−0.627***	−0.628***	−0.626***	−0.627***
	(0.049)	(0.049)	(0.054)	(0.049)
Observations	559,073	559,073	559,073	559,073
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.363	0.363	0.363	0.363
Adjusted R^2	0.343	0.343	0.343	0.343
Residual Std. Error (df = 542204)	4.134	4.133	4.135	4.134
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.11: Interaction Models: Log-PCGDP, corruption and global forests

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Democracy (BMR)	−1.326***	−0.902***	−1.192***	−1.190***
	(0.353)	(0.319)	(0.352)	(0.314)
Rural supporters	−1.369**			
	(0.513)			
Democracy x Rural supporters	1.526**			
	(0.743)			
Urban supporters		−0.243		
		(0.571)		
Democracy x Urban supporters		−0.235		
		(0.684)		
Agrarian elites (most important)			1.409	
			(1.313)	
Democracy x Agrarian elites			−1.319	
			(1.324)	
Business elites (most important)				−1.589**
				(0.685)
Democracy x Business elites				0.713
				(0.662)
Ln Per capita GDP (t-1)	0.952***	0.932***	0.930***	0.972***
	(0.272)	(0.273)	(0.271)	(0.285)
Δ Per capita GDP (t-1)	−15.304	−16.117	−12.446	−16.947
	(13.638)	(13.390)	(13.963)	(14.096)
Δ Population growth (t-1)	0.034	−0.007	−0.005	0.010
	(0.194)	(0.177)	(0.187)	(0.188)
Political corruption (V-dem) (t-1)	0.255	0.201	0.542	0.633
	(3.080)	(3.003)	(3.177)	(3.177)
Executive corruption (V-dem) (t-1)	−2.716	−2.746	−2.982	−2.585
	(1.888)	(1.908)	(1.964)	(1.929)
Forest (t-1)	−0.660***	−0.660***	−0.660***	−0.660***
	(0.047)	(0.047)	(0.046)	(0.046)
Observations	1,540,553	1,540,553	1,540,553	1,540,553
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.369	0.368	0.368	0.369
Adjusted R^2	0.347	0.346	0.346	0.347
Residual Std. Error (df = 1488977)	3.840	3.841	3.842	3.838
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.12: Interaction Models: Log-PCGDP, corruption and tropical forests

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Democracy (BMR)	−0.325	−0.273	−0.266	−0.438
	(0.302)	(0.285)	(0.297)	(0.356)
Rural supporters	−1.173*			
	(0.631)			
Democracy x Rural supporters	0.843			
	(0.779)			
Urban supporters		−0.691		
		(0.502)		
Democracy x Urban supporters		0.344		
		(0.637)		
Agrarian elites (most important)			1.449	
			(1.617)	
Democracy x Agrarian elites			−1.439	
			(1.598)	
Business elites (most important)				−1.576*
				(0.807)
Democracy x Business elites				1.169
				(0.763)
Ln Per capita GDP (t-1)	1.143**	1.099**	1.112**	1.160**
	(0.484)	(0.481)	(0.487)	(0.456)
Δ Per capita GDP (t-1)	−52.606**	−52.105**	−53.008**	−52.455**
	(24.953)	(25.400)	(25.089)	(24.794)
Δ Population growth (t-1)	−0.192	−0.234	−0.218	−0.150
	(0.214)	(0.212)	(0.207)	(0.180)
Political corruption (V-dem) (t-1)	4.463	4.419	4.680	4.491
	(2.853)	(2.775)	(2.909)	(2.849)
Executive corruption (V-dem) (t-1)	−2.426	−2.452	−2.644	−2.248
	(1.808)	(1.734)	(1.822)	(1.804)
Forest (t-1)	−0.636***	−0.635***	−0.635***	−0.636***
	(0.050)	(0.049)	(0.053)	(0.050)
Observations	541,421	541,421	541,421	541,421
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.367	0.367	0.367	0.368
Adjusted R^2	0.347	0.347	0.346	0.347
Residual Std. Error (df = 524556)	4.154	4.155	4.156	4.153
Note:				*p<0.1; **p<0.05; ***p<0.01

Support groups and global forests, country-level dependent variable

This test displayed in table A.9 uses the country-level dependent variable described in chapter 4 and replicates the tests in section 5.2. Note that only global forests are included as the country-level variable does not allow for differences in forest type. One noticeable aspect of using the country-level dependent variable is that the control variable per capita GDP is positive and significant at the 0.05 level. This indicates that when the geographic size of the the units are standardized (made identical), economic size is associated with increases in forests, in line with the EKC hypothesis.

Table A.13: Support groups and global forests, country-level

	Dependent variable:			
	forest.diff			
	(1)	(2)	(3)	(4)
Rural supporters	−0.254			
	(0.482)			
Urban supporters		−0.437		
		(0.389)		
Agrarian elites (most important)			0.846*	
			(0.450)	
Business elites (most important)				−0.236
				(0.521)
Per capita GDP (t-1)	0.079**	0.081**	0.080**	0.080**
	(0.033)	(0.033)	(0.034)	(0.033)
Δ Per capita GDP (t-1)	−1.211	−1.189	−1.130	−1.181
	(13.105)	(12.960)	(13.139)	(13.110)
Δ Population growth (t-1)	−0.069	−0.074	−0.070	−0.070
	(0.113)	(0.112)	(0.115)	(0.112)
Forest (t-1)	−0.619***	−0.620***	−0.618***	−0.618***
	(0.061)	(0.060)	(0.086)	(0.061)
Observations	4,669	4,669	4,669	4,669
Year fixed effects?	Yes	Yes	Yes	Yes
Cell fixed effects?	Yes	Yes	Yes	Yes
Clustered standard errors?	Yes	Yes	Yes	Yes
R^2	0.473	0.473	0.473	0.473
Adjusted R^2	0.168	0.168	0.168	0.168
Residual Std. Error (df = 2956)	3.275	3.274	3.275	3.275
Note:				*p<0.1; **p<0.05; ***p<0.01

Appendix B

Descriptive Statistics

Here I present descriptive statistics on the data set used in this theses. First, in table B.1, I present the variables included. Second, in table B.2, I present the summary statistics for the grid cell-level data set. Third, I include the summary statistics for the country-level data set in table B.3. Next, in figure B.1, I include a correlation matrix of the included variables, showing how much the different variables are correlated with one another. Figure B.2 shows the distribution of democracies and autocracies measured with the BMR measure of democracy in the sample time-frame (1982 to 2016). Lastly, in table B.4 I include a table showing all the regimes included in the business elites sample.

Table B.1: List of Included Variables

Data set for analysis		
Variable	**Retrived from:**	**Measuring what?**
Dependent variables:		
Forest Change (0.5° grid cells)	Song et al. (2018) & Sanford (2021)	Deforestation/Reforestation
Forest Change (country aggregated)	Song et al. (2018) & Sanford (2021)	Deforestation/Reforestation
Independent variable:		
Democracy (BMR)	Boix, Miller and Rosato (2018)	Democracy/democratization
Moderation variables:		
Rural Supporters ($\geq$ 0.5)	Coppedge et al. (2021)	Rural coalition identity
Urban Supporters ($\geq$ 0.5)	Coppedge et al. (2021)	Urban coalition identity
Agrarian elites (most important)	Coppedge et al. (2021)	Elite dominated coalition
Business elites (most important)	Coppedge et al. (2021)	Elite dominated coalition
Rural Support Location	Coppedge et al. (2021)	Location of coalition
Urban Support Location	Coppedge et al. (2021)	Location of coalition
Control variables:		
PCGDP, lagged ($USD)	WB (2017)	Economic activity
Δ PCGDP, lagged	WB (2017)	Economic activity (% change)
Population, lagged	WB (2017)	Population size (% change)
Polyarchy	V-Dem/Coppedge et al. (2021)	Democracy
Forest (lagged)	Song et al. (2018) & Sanford (2021)	Forest last year

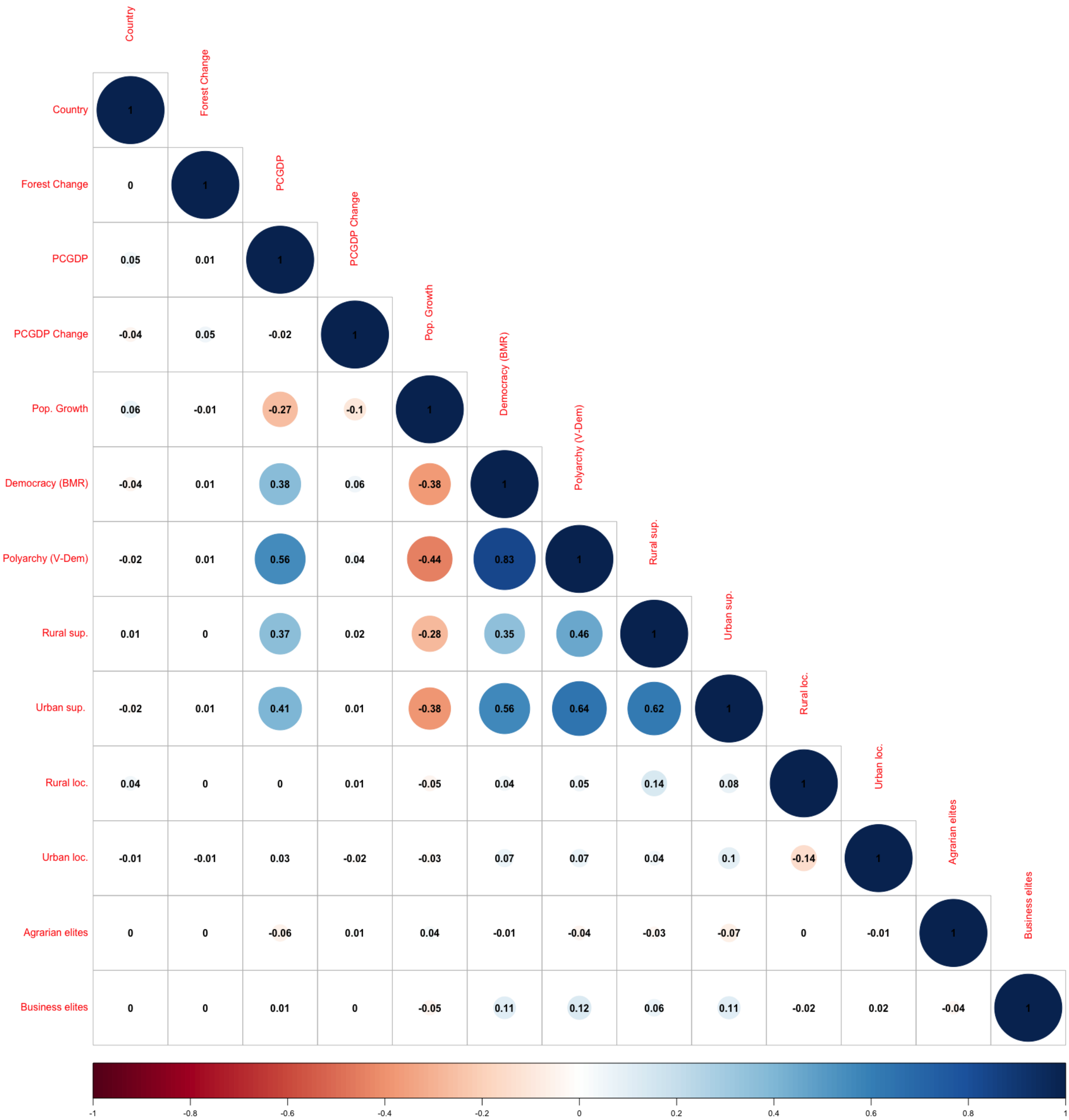
Table B.2: Summary Statistics (Cell-level)

Variable name	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Forest (% t-1 to t+0)	1740277	0.01	4.709	-53.82	-1.55	1.55	48.32
Forest (% t-1)	1740277	27.078	27.196	0	2.645	46.53	97
Forest (%)	1787050	27.188	27.211	0	2.7	46.69	97
PCGDP (t-1)	1604273	0.002	0.005	-0.065	0	0.005	0.141
Δ PCGDP (t-1)	1616512	17.521	18.019	0.132	3.415	35.305	111.968
Δ Pop. growth (t-1)	1738338	1.116	0.99	-6.185	0.522	1.573	14.237
Democracy (BMR)	1705252	0.568	0.495	0	0	1	1
Rural supporters	1787050	0.286	0.452	0	0	1	1
Urban supporters	1787050	0.455	0.498	0	0	1	1
Agrarian elite (mimp)	1787050	0.009	0.092	0	0	0	1
Business elite (mimp)	1787050	0.052	0.221	0	0	0	1
Rural location	1787050	0.182	0.386	0	0	0	1
Urban location	1787050	0.116	0.321	0	0	0	1

Table B.3: Summary Statistics (Country-level)

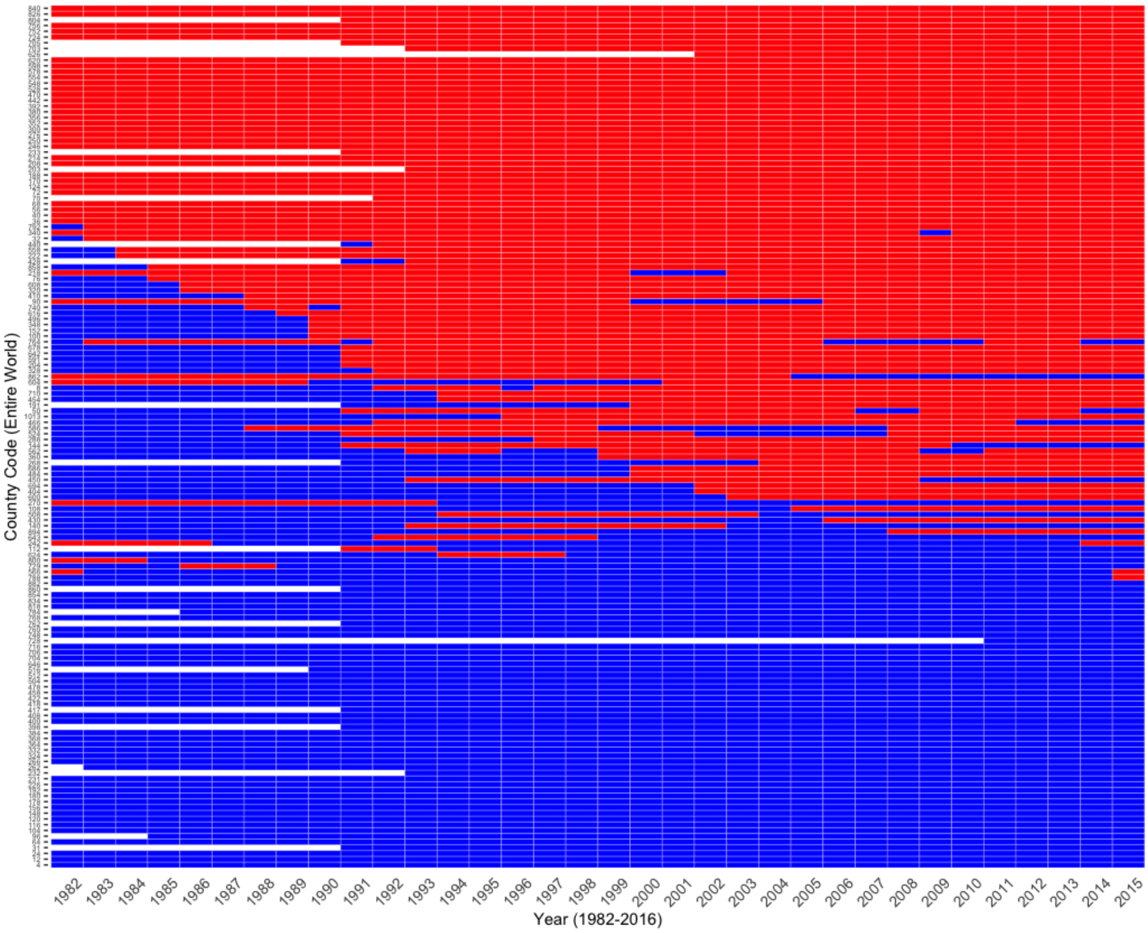
Variable name	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Forest (% t-1 to t+0)	5573	0.059	3.712	-24.373	-1.398	1.48	22
Forest (% t-1)	5573	31.848	23.373	0	11.276	48.955	94.545
Forest (%)	5735	31.938	23.37	0	11.33	49.034	94.545
PCGDP (t-1)	4713	10.669	16.869	0.132	1.003	10.614	111.968
Δ PCGDP (t-1	4739	0.002	0.006	-0.065	0	0.004	0.141
Δ Pop. growth (t-1)	5312	1.657	1.425	-6.185	0.634	2.64	14.237
Democracy (BMR)	4875	0.499	0.5	0	0	1	1
Rural supporters	5735	0.26	0.439	0	0	1	1
Urban supporters	5735	0.339	0.473	0	0	1	1
Agrarian elites (mimp)	5735	0.011	0.105	0	0	0	1
Business elites (mimp)	5735	0.101	0.302	0	0	0	1
Rural location	5735	0.098	0.298	0	0	0	1
Urban location	5735	0.156	0.363	0	0	0	1

Figure B.1: Correlation Matrix of Included Variables (Country-level)



The above correlation matrix displays the covariation between the different variables used in this thesis measured in pearsons product-moment correlation coefficient (PPC). Notable trends here are that the BMR measure of democracy correlates significantly with the Polyarchy (V-Dem) measure, and that rural and urban groups correlate significantly. This validates the strategy of regressing the different support groups individually on forest change (used in chapter 5).

Figure B.2: Democracy and autocracy, 1982 to 2016 (BMR)



In red, countries coded as democratic in their respective country-year by Boix et al. (2013), while countries in blue are coded as autocratic. The rectangles in white represents missing values. The y-axis covers all the countries in the data set, denoted by UN's M49 country-codes, included as the variable "UN_ccode" in the data set. On the x-axis are the years included in the dataset, included as the "year" variable in the data set. A brief look at the above graph shows a relatively even rate of democratization (except a jump following the collapse of the USSR), with a slowing rate in the mid 2000s.

Table B.4: Business Elites Dominating the Support Coalition 1982 to 2016 (Years)

	Country	Regime (v2reginfo)	Business Elite-Years
1	Albania	Post-1992 Albania (10/04/1992 - E)	4
2	Austria	Austrian Second Republic (14/04/1945 - E)	1
3	Bangladesh	2008-2014 constitutional alternation (07/01/2009 - 05/01/2014)	3
4	Botswana	Independent Botswana under the BDP (01/10/1966 - E)	9
5	Bulgaria	Republic of Bulgaria (13/07/1991 - E)	24
6	Chile	Post-1988 transitional period (31/07/1989 - 11/03/1990)	1
7	Chile	Republic of Chile (12/03/1990 - E)	27
8	Chile	The constitutional Pinochet period (12/03/1981 - 30/07/1989)	7
9	Colombia	Post-National Front (08/08/1974 - 04/07/1991)	8
10	Costa Rica	Post-1949 constitutional period (08/11/1949 - E)	8
11	Czech Republic	Czech Republic (01/01/1993 - E)	11
12	Djibouti	RPP's Djibouti (under Gouled and Guelleh) (25/10/1981 - E)	27
13	Dominican Republic	Post-1979 constitutional alternation of presidents (17/08/1979 - E)	30
14	Ecuador	Post- 1979 constitutional rule (11/08/1979 - E)	8
15	Ecuador	Post- 2008 constitutional rule (11/08/1979 - E)	1
16	Fiji	Bainimarama's constitutional rule (08/09/2013 - E)	2
17	Georgia	Post-1992 Georgia (03/01/1992 - 24/08/1995)	3
18	Georgia	Post-Rose Revolution Georgia (24/11/2003 - E)	4
19	Georgia	Shevardnadze's Georgia (25/08/1995 - 23/11/2003)	6
20	Germany	West Germany (24/05/1949 - 03/10/1990)	8
21	Greece	The Third Hellenic Republic (12/06/1975 - E)	7
22	Haiti	Avril's rule (18/09/1988 - 10/03/1990)	2
23	Haiti	Cedras' rule (01/10/1991 - 08/10/1994)	3
24	Haiti	Duvaliers' Haiti (23/10/1957 - 07/02/1986)	4
25	Haiti	Interim Military Administration 86-88 (08/02/1986 - 20/06/1988)	2
26	Haiti	Return of elected executives 1994 - (09/10/1994 - 07/02/2001)	7
27	Haiti	Transitional government 1990-1991 (11/03/1990 - 07/02/1991)	1
28	Hungary	Post-Communist Hungary (24/10/1989 - 01/01/2012)	20
29	Indonesia	Indonesia under its 2002 constitution (11/08/2002 - E)	1
30	Kyrgyzstan	Bakiyev's presidency (15/08/2005 - 08/04/2010)	1
31	Kyrgyzstan	Parliamentary Republic of Kyrgyzstan (28/06/2010 - E)	7
32	Madagascar	The Second Malagasy Republic (22/12/1975 - 31/10/1991)	3
33	Madagascar	The Third Malagasy Republic (20/08/1992 - 17/03/2009)	7
34	Malawi	Malawi since 1993 constitution (17/05/1994 - E)	14
35	Mexico	PRI Mexico (02/12/1928 - 02/07/2000)	5
36	Mongolia	Post-1992 constitution (13/02/1992 - E)	6
37	Mozambique	Independent Mozambique - Frelimo rule (26/06/1975 - E)	23
38	New Zealand	Post-1893 Act (20/09/1893 - E)	21
39	Niger	Democratic interlude in Niger (23/01/1993 - 21/01/1996)	3
40	Niger	Kountche/Seibou's Niger (15/04/1974 - 22/01/1993)	1
41	Niger	Mainassara civilian rule (13/05/1996 - 09/04/1999)	3
42	Niger	Post-2011 constitutional rule (08/04/2011 - E)	1
43	Niger	Tandja's government (19/07/1999 - 26/06/2009)	10
44	Niger	Tandja's self-coup (27/06/2009 - 18/02/2010)	1
45	Nigeria	Babangida's rule (28/08/1985 - 26/08/1993)	8
46	Nigeria	Buhari's rule (01/01/1984 - 27/08/1985)	1
47	Nigeria	Military rule 1993-1999 (18/11/1993 - 29/05/1999)	6
48	Nigeria	Post- 1999 alternation (30/05/1999 - E)	18
49	Nigeria	Shagari's presidency (02/10/1979 - 31/12/1983)	2
50	Oman	Sultanate of Oman (02/01/1749 - E)	35
51	Pakistan	Alternation post-2008 (19/08/2008 - E)	3
52	Pakistan	Elected government 1988 - 1993 (03/12/1988 - 18/07/1993)	1
53	Pakistan	Elected government 1993 - 1998 (20/10/1993 - 28/05/1998)	1
54	Pakistan	Sharif's state of emergency (29/05/1998 - 12/10/1999)	1
55	Papua New Guinea	Independent Papua New Guinea (17/09/1975 - E)	7
56	Paraguay	Republic of Paraguay (21/06/1992 - E)	14
57	Paraguay	Rodriguez post-coup government (04/02/1989 - 20/06/1992)	2
58	Peru	1979 constitutional period (13/07/1979 - 05/04/1992)	2
59	Peru	Constutional and alternating governments since 2001 (29/07/2001 - E)	16
60	Peru	Fujimori's Peru (06/04/1992 - 22/11/2000)	8
61	Peru	Interim government under Paniagua (23/11/2000 - 28/07/2001)	1
62	Poland	Post-Communist Poland - the third Republic (05/06/1989 - 02/04/1997)	7
63	Poland	Republic of Poland - "the fourth Republic" (03/04/1997 - E)	19
64	Russia	Russian Federation (22/09/1993 - 04/03/2012)	1
65	Serbia	Confederation of Serbia and Montenegro (05/02/2003 - E)	14
66	Serbia	Serbia part of Federal Republic of Yugoslavia (28/04/1992 - 04/02/2003)	2
67	South Africa	ANC-dominated years (05/02/1997 - E)	5
68	Spain	1978 constitutional monarchy (07/12/1978 - E)	8
69	Switzerland	Post-1971 referendum (08/02/1971 - E)	35
70	Thailand	1977-1988 Period of strengthened parliament (21/10/1977 - 24/07/1988)	1
71	Thailand	1988-1991 civilian interlude (25/07/1988 - 23/02/1991)	1
72	Thailand	Post-1997 constitution (12/10/1997 - 19/09/2006)	4
73	Turkey	Post-1982 constitutional Republic of Turkey (08/11/1982 - 16/04/2017)	6
74	Uzbekistan	Republic of Uzbekistan (27/12/1991 - E)	7

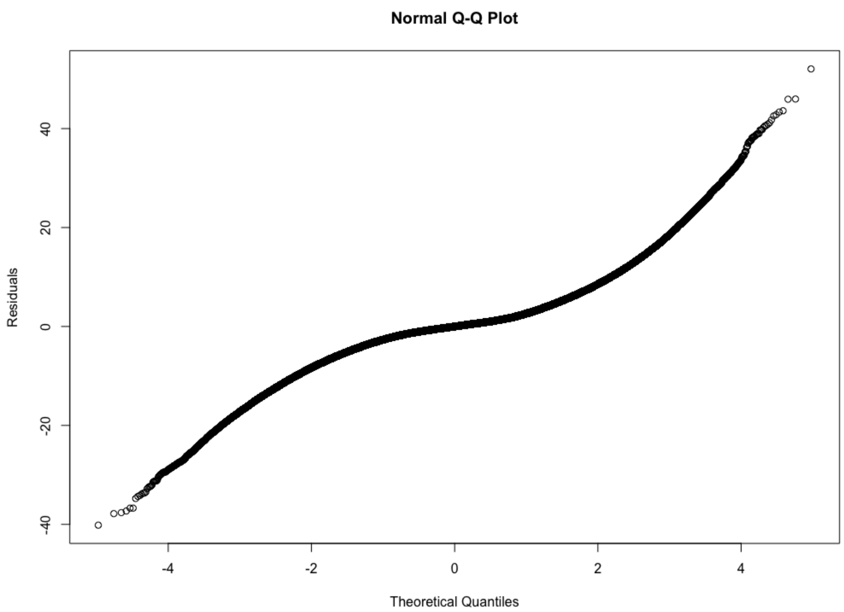
Appendix C

Diagnostics and Estimates

Q-Q Plot, Residual Standard Errors

The Q–Q (quantile-quantile) plot a graphical method for comparing two probability distributions by plotting their quantiles against each other. Here, the set of intervals for the quantiles are chosen. A point (x, y) on the plot corresponds to one of the quantiles of the second distribution (y-coordinate) plotted against the same quantile of the first distribution (x-coordinate). Thus the line is a parametric curve with the parameter which is the number of the interval for the quantile. The plot can be used to measure the agreement of a fitted distribution (in this case a Gaussian distribution), with observed data. Eyeballing the plot suggests that the model is heavy-tailed, which OLS is not particularly sensitive for, but may yield some bias as observations far from the mean value are excessively penalized by the model.

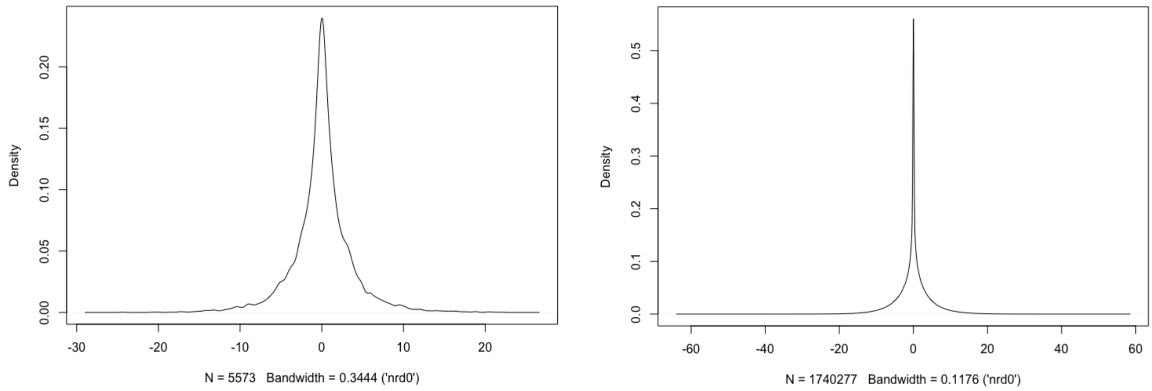
Figure C.1: Q-Q Plot, Residual Standard Errors (M1 Ru)



Kernel Density Estimation (KDE) Plots of Dependent Variables

The KDE plots is a method for visualizing the distribution of observations in a dataset, analagous to a histogram. In figure C.1 I visualize the distribution of the dependent variable (forest cover change) for both the cell-level data set (right-side) and the country-aggregated data set (left-side). As seen below, the dependent variable expresses a somewhat normal distribution with heavy tails.

Figure C.2: KDE plots, Forest Cover Change (Country- and Cell-level)



Matching: Average Treatment Effect on the Treated (ATT), Urban Groups

```
### Urban supporters: 3-Year pre-treatment match
Weighted Difference-in-Differences with Mahalanobis Distance
Matches created with 3 lags

Standard errors computed with 1000 Weighted bootstrap samples

Estimate of Average Treatment Effect on the Treated (ATT) by Period:
$summary
       estimate  std.error        2.5%    97.5%
t+0   0.1059840  1.1574796  -2.3492932 2.044193
t+1   1.0017231  0.7728903  -0.5330645 2.492615
t+2  -0.1557643  1.0280017  -2.3858567 1.594977
t+3   0.1569347  0.8507526  -1.6429678 1.684028

### Urban supporters: 5-Year pre-treatment match
Weighted Difference-in-Differences with Mahalanobis Distance
Matches created with 5 lags

Standard errors computed with 1000 Weighted bootstrap samples
```

```
Estimate of Average Treatment Effect on the Treated (ATT) by Period:
$summary
        estimate std.error         5%      95%
t+0   0.24900558 1.1528770 -1.6515951 2.138276
t+1   0.91687113 0.8692289 -0.4315801 2.324068
t+2  -0.37039613 1.1345522 -2.2940718 1.440881
t+3  -0.05444138 0.9171158 -1.5655259 1.442467
```

Matching: Average Treatment Effect on the Treated (ATT), Business Elites

```
### Business elites: 3-Year pre-treatment match
Weighted Difference-in-Differences with Mahalanobis Distance
Matches created with 3 lags

Standard errors computed with 1000 Weighted bootstrap samples

Estimate of Average Treatment Effect on the Treated (ATT) by Period:
$summary
        estimate std.error      2.5%      97.5%
t+0  -0.54014298 1.0566565 -2.834096 1.28431407
t+1  -0.01068106 1.2357622 -2.576076 2.38097570
t+2  -0.44504861 0.8029824 -2.187718 1.03008457
t+3  -1.33554460 0.7149601 -2.822539 0.02710116

### Business elites: 5-Year pre-treatment match
Weighted Difference-in-Differences with Mahalanobis Distance
Matches created with 5 lags

Standard errors computed with 1000 Weighted bootstrap samples

Estimate of Average Treatment Effect on the Treated (ATT) by Period:
$summary
        estimate std.error        5%        95%
t+0  -0.40848294 1.0945233 -2.411156  1.2615607
t+1   0.01267895 1.2082891 -2.223309  1.6743640
t+2  -0.32891170 0.7973234 -1.626082  0.9558570
t+3  -1.24529417 0.7439938 -2.546609 -0.1091752
```

Appendix D

VIF Tests

Variance inflation factor (VIF) tests are performed in order to test if there are multicollinearity in the regression models. Usually, VIF values below 5 are considered low, values over 5 are considered moderate to high, while over 10 are very high.

Table D.1: VIF Test M2 Ru (Table 5.1)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.45	1.20
2	Δ Per capita GDP (t-1)	1.44	1.20
3	Δ Population growth (t-1)	1.13	1.06
4	Rural supporters	1.15	1.07
5	Democracy (BMR)	1.12	1.06

Table D.2: VIF Test M3 Ur (Table 5.1)

	Term	VIF	SE_factor
1	Per capita GDP (t-1)	1.80	1.34
2	Δ Per capita GDP (t-1)	1.39	1.18
3	Δ Population growth (t-1)	1.08	1.04
4	Urban supporters	2.08	1.44
5	Democracy (BMR)	1.63	1.28

Table D.3: VIF Test M4 Ae (Table 5.1)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.54	1.24
2	Δ Per capita GDP (t-1)	1.42	1.19
3	Δ Population growth (t-1)	1.07	1.04
4	Agrarian elites	1.14	1.07
5	Democracy (BMR)	1.12	1.06

Table D.4: VIF Test M5 Be (Table 5.1)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.43	1.20
2	Δ Per capita GDP (t-1)	1.62	1.27
3	Δ Population growth (t-1)	1.07	1.03
4	Business elites	1.52	1.23
5	Democracy (BMR)	1.31	1.14

Table D.5: VIF Test M2 Ru (Table 5.2)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.26	1.12
2	Δ Per capita GDP (t-1)	1.12	1.06
3	Δ Population growth (t-1)	1.44	1.20
4	Rural supporters	1.23	1.11
5	Democracy (BMR)	1.85	1.36

Table D.6: VIF Test M3 Ur (Table 5.2)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.23	1.11
2	Δ Per capita GDP (t-1)	1.69	1.30
3	Δ Population growth (t-1)	1.28	1.13
4	Urban supporters	1.55	1.25
5	Democracy (BMR)	1.55	1.25

Table D.7: VIF Test M4 Ae (Table 5.2)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.25	1.12
2	Δ Per capita GDP (t-1)	1.11	1.06
3	Δ Population growth (t-1)	1.44	1.20
4	Agrarian elites	1.21	1.10
5	Democracy (BMR)	1.72	1.31

Table D.8: VIF Test M5 Be (Table 5.2)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.25	1.12
2	Δ Per capita GDP (t-1)	1.26	1.12
3	Δ Population growth (t-1)	1.52	1.23
4	Business elites	1.28	1.13
5	Democracy (BMR)	1.61	1.27

Table D.9: VIF Test M1 Ru (Table 5.3)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.15	1.07
2	Δ Per capita GDP (t-1)	1.26	1.12
3	Δ Population growth (t-1)	1.19	1.09
4	Rural supporters	1.12	1.06

Table D.10: VIF Test M2 Ur (Table 5.3)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.43	1.20
2	Δ Per capita GDP (t-1)	1.24	1.11
3	Δ Population growth (t-1)	1.06	1.03
4	Urban supporters	1.23	1.11

Table D.11: VIF Test M3 Ae (Table 5.3)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.29	1.14
2	Δ Per capita GDP (t-1)	1.25	1.12
3	Δ Population growth (t-1)	1.17	1.08
4	Agrarian elites	1.21	1.10

Table D.12: VIF Test M4 Be (Table 5.3)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.17	1.08
2	Δ Per capita GDP (t-1)	1.23	1.11
3	Δ Per capita GDP (t-1)	1.11	1.06
4	Business elites	1.08	1.04

Table D.13: VIF Test M1T Ru (Table 5.4)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.12	1.06
2	Δ Per capita GDP (t-1)	1.05	1.03
3	Δ Population growth (t-1)	1.08	1.04
4	Rural supporters	1.01	1.01

Table D.14: VIF Test M2T Ur (Table 5.4)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.18	1.09
2	Δ Per capita GDP (t-1)	1.20	1.10
3	Δ Population growth (t-1)	1.16	1.08
4	Urban supporters	1.33	1.15

Table D.15: VIF Test M3T Ae (Table 5.4)

	Term	VIF	SE factor
1	Per capita GDP (t-1)	1.18	1.09
2	Δ Per capita GDP (t-1)	1.04	1.02
3	Δ Population growth (t-1)	1.14	1.07
4	Agrarian elites	1.15	1.07

Table D.16: VIF Test M4T Be (Table 5.4)

	Term	VIF	SE_factor
1	Per capita GDP (t-1)	1.12	1.06
2	Δ Per capita GDP (t-1)	1.19	1.09
3	Δ Population growth (t-1)	1.22	1.11
4	Business elites	1.30	1.14