University of Milan and University of Pavia
Ph.D in Economics
XXXIV Cycle

Essays on the Political Economy of Environmental Policies and International Trade

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Academic Year 2021/2022

Acknowledgements

I am indebted to numerous people who have accompanied me through this long journey. I would especially like to thank Natalia and our families for supporting me and encouraging me to pursue a PhD. Their patience and understanding have been a source of inspiration and energy during this process. Many thanks go to my lifelong friends for their continuous friendship, advice, and laughs when most needed.

A special thank you goes to professor Alessandro Olper, my supervisor, who guided me with invaluable and generous advice. He has been a unique source of motivation and inspiration, professionally and personally. I would like to thank the coordinators of the PhD program for their dedication and support, as well as my doctoral colleagues with whom I have shared the experience. Many thanks go to the professors and researchers of the University of Milan and University of Pavia with whom I had the opportunity to collaborate. It has been a long but worthy journey.

Declaration of Authorship

I, Paolo Bonnet, declare that this thesis titled, "Essays on the Political Economy of Environmental Policies and International Trade", and the work presented in it are my own. This work was mainly done while in candidature for a Ph.D. degree in Economics at the University of Milan and University of Pavia.

I confirm that Chapter 1 was jointly co-authored with Alessandro Olper. Alessandro and I conceived the original idea and collected the data employed in the analysis. I performed the empirical analysis and drafted the text under his supervision and guide. Chapter 2 is not co-authored and is the result of my own work.

I acknowledge all main sources of help from the professors and researchers of the Department of Environmental Science and Policy of the University of Milan, of the Department of Economics, Management and Quantitative Methods of the University of Milan, and of the Department of Economics and Management of the University of Pavia. In particular, I would like to thank Marzio Galeotti, Riccardo Puglisi, Marcella Nicolini, Daniele Curzi and the two anonymous referees of my doctoral thesis for providing useful suggestions for my research activity and invaluable support.

All mistakes remain my own.

Contents

Introduction

Over the past decades, the scientific evidence on human-induced climate change has boomed. According to the latest special report of the Intergovernmental Panel on Climate Change, human activities are estimated to have caused a global warming of approximately 1°C (likely between 0.8°C and 1.2 °C) in 2017 above pre-industrial levels [IPCC (2018)]. Without substantial reduction in carbon emissions, the risk of major disruptions in natural ecosystems associated with serious impacts on economic activities will keep rising.

The 2015 Paris Agreement and its finalization in November 2021 with the Glasgow Climate Pact constitute a remarkable diplomatic achievement for the global consensus to limit global warming within the 1.5°C target. At the Glasgow COP26 Conference, for the first time, countries agreed to phase down unabated coal power and subsidies for fossil fuels. However, the voluntary approach of such international agreements undermines the credibility of their ambitions. Indeed, only sovereign national governments are ultimately responsible for translating climate commitments and promises into effective actions. How climate action depends on the political commitment of governments can be exemplified by the case of the United States. Just as President Trump decided to pull out of the agreement, the newly elected Biden administration quickly reversed this action by reentering in the agreement, while announcing ambitious promises over the climate agenda. Indeed, the efforts to fight climate change are widely fragmented internationally. While the European Union stands out with its ambitious strategy to reach carbon neutrality by 2050 (European Green Deal), there is a growing concern regarding the ability of large polluting countries to effectively ensure a sustainable development.

The reasons why there has been little progress in slowing emissions are well-known to economists. Multiple challenges plague climate mitigation, both for the global dimension of the problem and for the complexity of the responses required to tackle it. International climate policy has mostly proven to be ineffective due to the global free rider problem and to "carbon leakages". Thus, the efforts to reach the targets of the Paris agreement ultimately rely on effective national policies. As the negative externality of pollution is not reflected in market prices, government intervention is crucial to fix the climate externality through carbon pricing or through internalizing in the market the social benefits of clean energy. In addition, green transition entails the provision of another public good: innovations in low-carbon technologies. Only the diffusion and the development of carbon neutral technologies can ultimately lower mitigation costs. Nevertheless, like for all innovations, social returns are greater than private returns leading too little R&D spending for firms. Public policies need to provide special incentives for carbon neutral innovations as well.

Given the above dynamics, it appears clear the centrality of politics and technology in fighting climate change, as argued in a recent work of Besley and Persson (2020). In their framework, the key elements for the long-run transition to a sustainable economy lie on the interplay between politics, technology and values. If the success of climate actions passes by government intervention, then focusing on only optimal policy paths that ignore the importance of the underlying political process risks to be an infertile exercise. This is particularly true for climate policies that typically target expected long-term welfare gains and impose costs on the sources of polluting activities. On one side, policy preferences evolve along with the increased public awareness on global warming. For example, the salience of climate policy is progressively pushed at the heart of the political agenda of Western democracies. On the other side, political change may be restrained via lobbying activity by firms or economic actors that would be penalized by climate policies. But the opposition to climate actions diminishes as firms have access to carbon neutral technologies for their production process, or as the market for green technologies and products becomes larger and more attractive, and finally as green finance unlocks new business opportunities. While environmental policies and regulation can provide a first impetus for the deployment of green technologies whenever market forces give too little incentives to innovators, the rate and direction of technical change widely affects the cost-effectiveness of climate policies. The evolution of technology ultimately reduces the costs of climate mitigation and projects the production and consumption patterns into a long-run low-emissions path.

My dissertation, “Essays on the Political Economy of Environmental Policies and International Trade”, is inspired by the above considerations. It aims at bringing new empirical evidence to different strands of literature on political economy, innovation and international trade applied to the context of climate change. This thesis is composed of two chapters. The first one benefits from the contribution of my supervisor Alessandro Olper, while the second chapter is not co-authored. The two chapters are structured as stand-alone works, with their own background and research questions. However, the reader will find a link connecting the two chapters. That is the attempt to identify and analyze with an empirical approach which are the drivers of climate mitigation outcomes, either in the context of political outcomes or in the context of technical change. The focus on climate change is the compass that has driven my research interests during my doctoral studies.

The first chapter of my thesis, titled "Party affiliation, lobbying and the U.S. governors' renewable energy policies", adopts a political economy approach and empirically explores the interactions between political factors and lobbying influences in explaining the recent development of renewable energy sources in the United States. The main research objective is to investigate the role of the political economy determinants of renewable energy policies. Renewable energy deployment is particularly suited to be studied through the lens of a political economy approach given the centrality of public intervention in breaking the "carbon lock-in" of conventional energy sources and in accelerating the clean energy transition. Public support typically consists of production incentives, subsidies or mandatory regulations that are necessary to help renewable energy sources develop in the market. Moreover, the case of U.S. state renewable energy policies constitutes an ideal testing ground for a political economy study given the substantial autonomy of state governments in designing and implementing renewable energy policies and, more broadly, environmental policies.

Despite the centrality of public intervention, the role of the political economy determinants of renewable energy deployment has been rarely considered. Indeed, the literature has mostly focused on issues of effectiveness and efficiency of policy instruments for renewable energy sources [1]. Nevertheless, the political economy literature has extensively studied both theoretically and empirically the political economy forces of regulations and policies related to the environment [2].

A strand of the literature has focused on politicians' opportunistic behavior and electoral incentives. The seminal paper by List and Sturm (2006) shows that, in the area of environmental policies, US state governors strategically distort their policy preferences in order to attract votes to their platform and improve the probability of being re-elected. Focusing on party affiliation, the empirical work of

[1] See Bourcet (2020) for an extensive review of the literature.

[2] See Oates and Portney (2003) for an extensive review of the literature.

Fredriksson et al. (2011) brings evidence that politicians are primarily office motivated rather than driven by partisanship. These findings are consistent with the median voter theorem and with the "Downsonian" paradigm according to which politicians are only interested in winning offices [Downs (1957)]. However, the debate regarding politicians' motivations for public policies is still an outstanding research interest within the political economy literature. Recent theories depart from the assumptions of the median voter theorem and allow candidates to be purely policy-motivated [Callander (2008)]. Empirical results are mixed as well. For example, Kim and Urpelainen (2017) shed evidence on increasing partisan policy divergence in the U.S. federal climate policy. Another strand of the political economy literature has studied the interactions of competing interest groups over environmental policies [Fredriksson (1997), Aidt (1998)]. The recent paper of Pacca et al. (2021) is of particular interest as it focuses on governors' party affiliation and their interactions with the political pressures by lobby groups in order to study U.S. environmental policies.

Drawing from the existing contributions on party affiliation and lobbying, the first chapter of my dissertation aims at filling the gap in the literature on renewable energy deployment by complementing it with a political economy perspective. To the best of my knowledge, it is the first attempt to link politicians partisanship and lobbying influence to study renewable energy outcomes. The first research question regards the influence of US governors' party affiliation on renewable energy outcomes at the state level. The underlying hypothesis conceives that Democratic politicians are more prone to care about climate mitigation than Republicans. Thus, they are expected to increase the public support for renewable energy deployment. Using data on state renewable installed capacity and exploiting its variation across U.S. states, the first goal is to test whether the inter-party competition between Democratic and Republican governors translates into differences in renewable energy outcomes.

The second research question of the chapter involves the influence of lobbying pressures on the U.S. state environmental policies. The objective of the empirical analysis is to investigate whether governors' attitude towards renewable energy is enhanced or counteracted by lobbying activity. The empirical strategy is based on interacting governors' party affiliation with measures that capture the presence of lobby groups. The opposition to renewable energy sources is expected to increase within those groups that would loose the most from environmental policies that increase the electricity prices (such as public support for renewable energy). This group comprises manufacturing producers as their profits depend on the use of inexpensive electricity. The lobbying pressures of producers are proxied using several measures of industry size. Instead, renewable energy investors are expected to support renewable energy policies. Their relative political strength is proxied by the state level of renewable energy potential, assuming that their interests concentrate in those states where producing clean energy is more profitable.

The empirical results suggest that governor's party affiliation to the Democratic party had on average a positive impact on the state level of renewable capacity. During the period 1995-2010, renewable installed capacity has increased under Democratic governors as compared to Republican counterparts. However, the effect is highly heterogeneous across states and conditioned by the presence of other relevant political economy forces. Particularly, there is no evidence of policy divergence between governors from the two parties in states where the manufacturing industry is relevant or in states where the endowment of natural renewable resources is scarce. Thus, the results appear to be in line with those found by List and Sturm (2006), Fredriksson et al. (2011) and Pacca et al. (2021) in other areas of environmental policy. Overall, the evidence presented in the first chapter supports that politicians decisions over environmental policy primarily depend on re-election concerns and on the pressures by interest groups rather being determined by policy preferences.

The second chapter, titled "Foreign import competition and green innovation: the impact of Chinese trade exposure on technical change in Europe", focuses on foreign import competition and innovation with a novel attempt to link trade dynamics with the technological upgrading towards green inventions. It closely relates to the literature on international trade and innovation. Recently, the endogenous growth theory has expanded connecting innovation and participation in international markets through international trade [3]. Trade liberalization affects firms' profitability through several mechanisms: by providing new export opportunities, by bringing more import competition from abroad or through specialization according to comparative advantages. Within an endogenous growth approach, all these forces can affect the incentives to innovate for firms.

The second chapter focuses on only one among the forces: the effect of foreign import competition on innovation. Indeed, the question whether more competition spurs innovation is a long-standing interest in economic theory. From a theoretical standpoint, the most systematic effort to reconcile the Schumpeterian growth paradigm (according to which innovations are motivated by the prospects of monopoly rents) with the empirical evidence suggesting that a certain degree

[3] See Melitz and Redding (2021) for an extensive review of the literature.

of competition is growth-enhancing is carried out by Aghion et al. (2001) and Aghion et al. (2005). In their settings, increased product market competition can stimulate firms' innovation activity under certain circumstances. This occurs for example when firms compete at similar technology levels and, therefore, they have an incentive to escape from the competition of the rivals by innovating more. At the same time, more competition stifles innovation for laggard firms as they have lower chances to catch up with their competitors' technology.

The ambiguity in the relationship between competition and innovation is also reflected in the still puzzled empirical evidence. Several recent contributions have focused on the China trade boom given that it was the main recent shock to the Northern economies in terms of increased competitive pressure from abroad. Bloom et al. (2016) provide evidence on an overall positive effect of increased Chinese import competition on the technological advancement of European firms. Conversely, Autor et al. (2020) found that the rising competitive pressure from China had an adverse effect on the innovation of domestic firms in the United States.

Drawing from the works of Bloom et al. (2016) and Autor et al. (2020), the second chapter of this thesis empirically examines the impact of Chinese import competition on technical change in Europe. There are two main contributions of my work. First, I bring additional evidence to the debate on the relationship between competition and innovation by focusing on industry-level measures of technical change in thirteen European countries. Second, I attempt to explore a new field of research on trade and green specialization by hypothesizing that the China trade shock might have accelerated innovation in green products in Europe. To the best of my knowledge, this aspect has not been previously investigated. The idea of focusing on green innovations is not only motivated by the importance of studying the dynamics of green technological advancement in the context of the climate challenge but also because green technologies require high-tech capabilities to be developed. Bontadini and Vona (2020) provide detailed evidence that green production is highly concentrated in high-tech industries. Thus, in this context, green specialization entails both technological upgrading and the achievement of sustainable goals.

The methodology makes use of patent data from PATSTAT [4] to construct growth rates of industry-wide patent stocks. Trade data are employed to capture changes of Chinese import competition. By exploiting the detailed information re-

[4] PATSTAT is the data set on patents for statistical analysis that was developed by the European Patent Office.

garding innovations' technology fields, it is possible to construct industry-specific measures of patents' growth in green inventions to be compared with the growth rates in total generic innovations. When estimating the impact of rising Chinese imports at the industry level, I find no effect on total innovation but a significant and positive effect on green innovation. This suggests that the China trade shock accelerated green technical change in manufacturing European industries. I employ an instrumental variable approach similar to the one developed by Autor et al. (2014). The strategy relies on instrumenting changes in Chinese imports in the European industries with contemporaneous changes in industry imports in other OECD countries. The instrumental variable strategy is therefore useful to purge for the endogeneity of trade exposure. Interestingly, the effect appears to be stronger in industries lagging behind the technology frontier. This seems to be explained by a within-sector reallocation effect: increased competition from China pushed out the market low-tech firms while shifting innovation from low-tech to high-tech firms.

The findings presented in the second chapter add evidence to the research on the relationship between competition and innovation but with novel insights on green specialization. The focus on trade, competition and the environment is rather unexplored and makes it possible for my work to be further developed in different directions. Indeed, the findings relate to different strands of the literature beyond competition and innovation. First, my work relates to the research on international trade and the environment. Recent contributions on the relationship between international trade and environmental outcomes have shown how the technique effect (i.e., reduction in pollution emitted per unit of output) mainly affects changes in emissions [5]. The technique effect is, in turn, driven by a variety of forces such as tightening of environmental regulation or within-industry reallocation to cleaner plants that can be induced by increased import competition or productivity growth. However, while the literature has mostly focused on the "pollution haven hypothesis", there is little work studying the impact of increased trade on environmental outcomes [6]. To the best of my knowledge, there are no contributions linking trade with innovation in green technologies. My work aims at shedding more light on a possible unexplored effect of trade on fostering green innovations.

Finally, the endogenous theory of growth has been extended to study the

[5] See Copeland et al. (2021) for an extensive literature review.

[6] An important contribution is the one of Bombardini and Li (2020) that, based on comparative advantages, identify the effect of increased exports on regional pollution and infant mortality in China.

drivers of directed technical change in green technologies [7]. While my results disclose an interesting effect of trade on green innovation, the impact and interactions with other drivers of directed-technical change are not part of the analysis. Thus, a natural direction that my work could take would be to integrate these factors into future research.

[7] An early empirical work is Popp (2002). Theoretical contributions on directed technical change applied to the environment come from Acemoglu et al. (2012) with later work by Acemoglu et al. (2016) and Aghion et al. (2016).

CHAPTER 1

Party affiliation, lobbying and the U.S. governors' renewable energy policies

Abstract

This chapter investigates the influence of U.S. state governors' party affiliation and lobbying pressures by interest groups on renewable energy outcomes. Using data on the installed capacity from renewable energy sources, we find that Democratic governors had on average a positive impact on the state level of renewable energy. However, the effect is highly heterogeneous. Democratic governors do not promote more renewable energy as opposed to Republicans in states where the manufacturing industries are economically important or in states where the natural renewable endowment is scarce. Consistent with a political economy approach, we argue that in the area of renewable and climate policy, governors' policy preferences are overridden by holding office motivations and lobbying pressures.

1.1 Introduction

In the global response to tackle climate change, renewable energy transition has emerged as an important strategy adopted to decarbonize the power sector, which is a primary source of carbon dioxide emissions. Governments worldwide have introduced a wide array of public support schemes for renewable energy sources (RESs). Public intervention consists of production incentives, subsidies or mandatory regulations that are essential to break the "carbon lock-in" of conventional fossil fuel energy sources and develop renewable energy sources in the market[1].

[1] Some examples of these policies are renewable portfolio standards (RPSs), feed-in-tariffs, tax credits or investment grants. The common objective of government intervention is to ensure economic incentives to "non mature" energy sources in order to help them become cost competitive with conventional fossil fuel sources.

In the context of the United States, the efforts to promote clean energy have been mainly translated into the decentralized actions of state governments, given their substantial autonomy in deciding the stringency and scope of renewable energy policies and, more broadly, environmental policies.

The case of U.S. state renewable energy policies is not only policy relevant but also of particular interest for its political economy implications. Indeed, politicians' willingness to support renewable energy balances environmental goals with re-election concerns. Governors, who are the central actors in the policy making at the state level, are subject to the political pressures from alternative interest groups that act to influence the political agenda in their favor. Specifically, the sensitivity towards climate change has been increasing especially among Democratic voters by widening the partisan polarization over climate policy [2], as exemplified during the withdrawal of the U.S. federal government from the Paris Climate Agreement. On the other side, renewable energy policies have distributional impacts by raising the opposition or the support of different groups in the economy. Public intervention typically generates benefits for renewable energy investors while transferring the costs of cleaner energy and stringent environmental regulation to end-users in the form of higher energy prices or in the form of compliance burdens on the sources of polluting activities [3].

The political economy literature has extensively studied both theoretically and empirically the politicians' behavior and lobbying in the area of environmental policy [4]. The seminal paper by List and Sturm (2006) studies the role of electoral incentives on the US state governments environmental policies supporting that governors' behavior is mainly driven by opportunistic concerns for re-election. These findings are consistent with the strand of the "Downsonian" political economy literature that traditionally assumes politicians to be only interested in winning offices. Indeed, the controversial dispute on politicians' motivations for public policies is an open debate within the literature, while the empirical findings are still mixed. Focusing on party affiliation, Fredriksson et al. (2011) tested politicians' motivations in the area of environmental policies finding that

[2]See, for example, the survey by Pew Research Center at https://www.pewresearch.org/fact-tank/2020/02/28/more-americans-see-climate-change-as-a-priority-but-democrats-are-much-more-concerned-than-republicans/.

[3]Greenstone and Nath (2019) comprehensively evaluates the direct and indirect costs on the power system of renewable energy sources across the U.S. states. According to their study, average retail electricity prices increased by 17% in states 12 years after the adoption of a Renewable Portfolio Standard. The estimates take into account the charges on electricity bills to finance renewables incentives, the larger operational costs of renewable energy power plants and the indirect costs related to their intermittent energy production and to grid connections.

[4]For an extensive review of the literature see Oates and Portney (2003).

US governors are primarily office motivated rather than driven by partisanship. Conversely, Kim and Urpelainen (2017) shed evidence on increasing partisan policy divergence in the U.S. federal climate policy. A recent paper by Pacca et al. (2021) adds more complexity to the policy formation process by studying not only the impact of party affiliation on environmental policy but also its interactions with the political pressures from lobby groups.

Our analysis draws from the existing literature on party affiliation and lobbying but it focuses on an area where the empirical findings are still rather scarce: the case of the U.S. renewable energy deployment [5]. We exploit the variation across U.S. states in renewable energy outcomes to estimate the effects of political economy determinants. Using data on state renewable installed capacity, we first test whether the inter-party competition between Democratic and Republican governors translates into differences in renewable energy outcomes, hypothesizing that Democrats are more prone to care about climate mitigation than Republicans. Secondly, we investigate whether governors' attitude toward renewable energy is enhanced or counteracted by lobbying activity. This is empirically done by interacting governors' party affiliation with measures that capture the presence of lobby groups. Lobbying activity against renewable energy is proxied by alternative measures of the manufacturing industry size, as manufacturers' profits depend on the use of inexpensive energy. To capture the lobbying influence of renewable energy supporters, we exploit the exogenous variation in renewable energy resources (i.e., wind and solar potential) across the U.S. states, supposing that the interests of renewable energy investors concentrate in those states where producing clean energy is more profitable.

Our empirical results suggest that renewable installed capacity has increased under Democratic governors as compared to Republican counterparts for the period 1995-2010. This reveals some degree of policy diverge between the two parties. However, the effect is highly heterogeneous across states and conditioned by the context of where governors operate. In particular, the difference in renewable energy outcomes across Democratic and Republic governors shrinks as the state manufacturing industry size becomes larger. This suggests that, in states where the manufacturing industry is relevant, Democratic governors deviate from their own preferences and do not differ from Republicans in renewable energy achievements. Instead, we find that Democratic governors' willingness to promote renewable energy depends on the presence of renewable energy re-

[5] The contributions have in fact mostly focused on the effectiveness of renewable energy policies [see for example Menz and Vachon (2006), Carley (2009) and Delmas et al. (2016)].

sources. Overall, our evidence suggests that politicians' choices over renewable energy are influenced by holding office motivations and lobbying rather than determined by policy preferences. These results are in line with those found by List and Sturm (2006), Fredriksson et al. (2011) and Pacca et al. (2021) and they complement the growing literature on renewable energy sources with a political economy perspective.

We proceed with a review of the relevant literature in section 1.2. In section 1.3 we present a brief theoretical discussion of the possible behaviors of governors in the area renewable energy. In section 1.4 we discuss the empirical approach and describe the data employed. Section 1.5 and 1.6 report our main empirical results and some robustness tests, respectively. Finally, section 1.7 provides some concluding remarks.

1.2 Relevant Literature

The main contribution of our work is to explore whether renewable energy policies are driven by the partisan polarization in the American politics and to what extent special interest groups shape the policy outcome. In the area of renewable energy, the role of political-economy factors has been relatively disregarded. Overall, the literature has mostly focused on issues of effectiveness and efficiency of policy instruments for renewable energy sources or on the determinants of renewable energy deployment [6]. Menz and Vachon (2006) is one of the first econometric analysis examining the contribution to wind power development of several state-level policies in the United States. Carley (2009) empirically test the effectiveness of renewable portfolio standards in the U.S. states while Delmas and Montes-Sancho (2011) argued that the effectiveness of policy schemes largely depends on the natural, social and political context in which the policy is implemented. Only few studies, not related to the U.S. context, analyze the role of single political-economy factors. Cheon and Urpelainen (2013) and Cadoret and Padovano (2016) provide evidence showing that the presence of a strong manufacturing industry negatively affected renewable energy deployment using a sample of OECD countries and EU countries, respectively. Both works draw from Fredriksson and Millimet (2004) that investigate the relationship between corruption, industry size (as a proxy for lobby group size) and energy efficiency outcomes.

Our paper is closely related to the political economy literature on politicians'

[6] See Bourcet (2020) for a systematic literature review.

motivations guiding public policies. The seminal paper of List and Sturm (2006) is worth mentioning. They propose a theory of elections and supply of secondary policies (e.g., environment and trade policy). In their setting, incumbent politicians strategically distort their policy preferences in order to attract votes to their platform and improve the probability of being re-elected. By using data on the U.S. state environmental expenditures and exploiting the variation in gubernatorial term limits, they provide evidence confirming their hypothesis. Environmental policy differs between years in which governors can be reelected and years in which they face a term limit. In addition, in states classified as "brown" (i.e., where citizens have a lower sensitivity to the environment), re-electable governors undertake less environmental policy than governors facing a binding term, while the opposite pattern occurs in "green" states. Their main insight is that politicians' policy preferences are overridden by opportunistic concerns for re-election.

The findings of List and Sturm (2006) are consistent with the set of assumptions that have traditionally characterized the strand of the political economy literature drawing from the median voter theorem by Downs (1957). According to the "Downsonian" paradigm, candidates are solely interested in gaining votes and offices. Thus, their policy platforms reflect the median voter's preferences of each constituency rather than being shaped by partisan or ideological considerations. Conversely, another strand of the literature emphasizes politicians to be policy-motivated and interested in policy outcomes [Wittman (1983), Calvert (1985)]. As discussed in Persson and Tabellini (2002), this characteristic of the literature that develops following one or the other assumption represents an important limitation for the political economy literature.

This chapter adds new empirical evidence on this debate by explicitly studying the role of partisanship. We inform our work with theories that bridge the roles of holding office and policy motivations into a more realistic framework. In Alesina (1988), politicians pursue the implementation of their own preferred policy, not only winning elections. In a dynamic setting, divergence in policy outcomes across different parties is therefore possible under certain conditions (e.g., no commitment to electoral platforms, one-shot election games). More recently, Callander (2008) develops a theory of electoral competition where candidates may be either office or policy motivated. Voters are assumed to value policy-motivated candidates not only for their pre-election campaign platforms but also because they are likely to implement policies more effectively once elected. One key insight is that the strategic competition among heterogeneous types of candidates allows some margin of success to purely policy-motivated politicians even when their policy positions differ from the median voter's stance. In a similar spirit, Kartik and Preston Mcafee (2007) present a model where some candidates have an exogenous policy preference called "character" that is valued by voters as a signal of reliable policy commitment. Thus, even strategic candidates imitate politicians with character and move away from the median voter's ideal point in order to gain credibility from voters. Cremer et al. (2008) tries to explain why U.S. environmental policies such as gasoline taxes have not incurred in substantial changes under Democratic or Republican governments with a model of partisan political competition. Building on Roemer (1999), Cremer et al. (2008) interpret the persistence of the U.S. environmental policy as one mainly driven by a stronger faction of "opportunistic" (i.e., office motivated) rather than "militant" (i.e., policy motivated) politicians in both the Democratic and Republican party.

Drawing from the theories above, several contributions empirically investigate politicians' motivations in the area of environmental policies. Fredriksson et al. (2011) move beyond the work of List and Sturm (2006) by studying the effect of U.S. governors' party affiliation on environmental expenditures [7]. They do so by comparing environmental expenditures not only across re-electable and "lame duck" governors [as in List and Sturm (2006)] but also across governors from the Democratic and Republican party. They find that there are no significant policy differences across governors from the two parties whenever they can run for another term (i.e., they have an incentive to act strategically rather choosing the preferred policy). They point out that this result is in contrast with what we should expect by assuming that politicians are purely policy-motivated and driven by partisan ideological differences. Thus, their evidence supports that politicians are primarily motivated by holding office and not by partisanship when they make decisions over environmental policies.

Conversely, Kim and Urpelainen (2017) support that the American environmental policy is highly polarized between the Democratic and the Republican party by studying the voting behavior of the congress members at the federal level. They find that the propensity to vote in favor of the environment increases substantially for elected Democratic congressmen as opposed to republican ones. Moreover, using a Regression Discontinuity Design (RDD), they attribute the causal effect to partisan ideological differences at the elite level rather than to disparities in the median voter's preferences across congressional districts. In other words, they argue that partisan elites are more polarized than public opin-

[7] Besley and Case (1993), Besley and Case (2003), List and Sturm (2006) and Fredriksson et al. (2011) constitute important contributions for the empirical literature on gubernatorial term limits, political institutions and policy outcomes in the United States.

ion over environmental issues. They also show that the polarization has increased over time and is particularly extreme for votes on issues related to climate change. Recently, Gagliarducci et al. (2019) bring new evidence regarding politicians' behavior over climate policies. They show that U.S. congress members are more prone to support climate legislation after their district has been hit by a hurricane. In light of the theories on populism, they argue that their willingness to promote environmental and climate policies depends on specific circumstances that facilitate them to choose policies with unpopular short-run costs and long-run benefits. The disaster of an hurricane is likely to increase the salience of climate change among voters inducing politicians for more action. In addition, they find that the response is stronger for politicians with electoral credit, with a pronounced pro-environmental ideology and elected in districts with better economic conditions.

This chapter is also related to the literature on public-choice and lobbying. One common limit of the works mentioned above is that they do not consider lobbying as a determinant of environmental policy, disregarding a key element of policy making. Besley and Coate (2001) propose to consider simultaneously electoral competition and lobbying. They integrate in one framework the citizen-candidate model of representative democracy and the "menu auction" model[8] of lobbying as introduced and applied to international trade by Grossman and Helpman (1994)[9]. Thereafter, the literature has developed by extending to different types of political contributions that politicians value for re-election. Lobbying influence is not only exerted through financing campaign contributions [as first postulated by Grossman and Helpman (1994)] but also through guaranteeing blocks of votes [Bombardini and Trebbi (2011)], persuading the public opinion [Yu (2005)] or providing information to policy-makers [Belloc (2015)].

The recent theory of environmental regulation has embedded a common-agency approach as well. A growing number of contributions focuses on the interactions of competing interest groups over environmental policy and on their implications for efficiency and social welfare [10]. Fredriksson (1997) builds on Grossman and Helpman (1994) and develops a model explaining how pollution

[8]The basic menu auction model was developed by Bernheim and Whinston (1986).

[9]The literature divides along two approaches. The political-support approach advanced by Grossman and Helpman (1994) envisions interest groups to offer political contributions to politicians in exchange of the implementation of determined policies. In contrast, the political competition approach stresses that contributions by lobbies are motivated to influence the election outcome rather than the policy [Hillman and Ursprung (1988)].

[10]For an extensive review of the theoretical and empirical political economy approaches in the domain of environmental policy, see Oates and Portney (2003).

tax policy is shaped by environmental and lobbying groups. Since governments determine policies so as to maximize aggregate social welfare and total contributions by lobbies, deviations from optimal level of the pollution tax rate (i.e., the Pigouvian tax rate) typically arise depending on lobby groups membership and government's relative weight on social welfare. Socially efficient policy equilibria are instead ideally achieved through the political process if all citizens have their interests represented by a lobby group, as argued by Aidt (1998). Aidt's model shows that the competition among lobbies is an important source of political internalization of economic externalities in the domain of environmental policies. Thus, government's failure in choosing socially efficient policies is the result of incomplete political internalization whenever some citizens do not gather their interests through organized lobby groups [11].

Within the growing literature on lobbying and environmental policies, the recent contribution by Pacca et al. (2021) is of particular interest. Their paper bridges the two seminal papers by List and Sturm (2006) and Yu (2005) by explicitly considering the role of lobbying pressures (and their interactions with political factors) in the policy formation process of environmental policies in the U.S. states. In their framework, governors' choices about the level of environmental expenditures (i.e., the outcome of the policy process formation) depend on their party affiliation and on the political contributions from environmentalist and industrialist interest groups, both of whom allocate resources to shift the policy outcome in their favor. Implementing a Regression Discontinuity Design (RDD), they identify and estimate the causal effect of electing a Democratic governor instead of Republican on the level of environmental expenditures. Consistently with their setting, they find that Democratic governors tend to decrease the environmental expenditures in states where the industrialist interest group constitutes a larger share of the economy. These results support the hypothesis that the lobbying pressures by interest groups influence governors' choices over environmental policies. Our work is therefore closely inspired by Pacca et al. (2021), both for what regards the theoretical background and the methodology.

More insights on the lobbying activity of industrial associations over the U.S. federal climate policy are growing within the empirical literature [12]. Meng and

[11] One explanation of this failure comes from the traditional theory of collective action. The theory suggests that only lobby groups that are less affected by the free-riding problem are more likely to emerge in the political arena [Olson (1965)]. It can explain why relatively small and homogeneous groups such as industrial or energy associations are considerably influential in the area of environmental policy.

[12] See also Brulle (2018) for a sectoral analysis of lobbying spending on climate change in the U.S.

Rode (2019) support that lobbying by firms expecting losses from climate policies was more effective than lobbying by firms expecting gains. Kim et al. (2016) find that the expected winners from climate bills (i.e., renewable energy and natural gas power generation) engaged in individual lobbying to shape specific provisions of the legislation while the expected losers (i.e., coal-intensive utilities) lobbied as a unified block against the legislation. Delmas et al. (2016) find that both dirty and clean firms are active in lobbying over climate policy while firms with intermediate carbon emissions have the least at stake in the policy outcome and, thus, devote fewer lobbying expenditures.

Finally, an interesting study on the link between public policies and rent seeking practices is proposed by Gennaioli and Tavoni (2016). They look at the case of wind energy. Their paper explores whether the presence of renewable natural resources led to an increase in corruption and illegal activities in the wind market. Using data on the Italian provinces, they find that high-wind provinces compared to non-windy provinces experienced an increase in criminal association activity after the introduction of public incentives for renewable energy. The evidence of Gennaioli and Tavoni (2016) inspires our work by showing how investors in renewable energy have a large interest at stake in contexts characterized by abundant renewable resources and, thus, they are more likely to lobby and bribe politicians for private exploitation of public subsidies.

1.3 Theoretical Background

Government intervention is essential to ensure clean energy transition. Environmental economists claim that pollution's costs are not reflected in energy prices without public regulation. Governments can correct this market failure by taxing fossil fuels on one side, and by supporting renewable energy, on the other. There are several barriers to renewable energy deployment. Government intervention is motivated to break the "carbon lock-in" of conventional energy sources that historically benefit of larger infrastructures, investments and scale economies with respect to newer technologies. Renewable energy policies aim at developing renewable energy sources in the market by increasing their profitability and competitiveness.

The decision of investing in renewable energy sources is therefore political. In the context of the United States, state governments have substantial autonomy in designing and implementing renewable energy policies [Menz and Vachon (2006), Carley (2009) and Delmas and Montes-Sancho (2011)] and, more broadly, environmental policies [List and Sturm (2006) and Pacca et al. (2021)]. Public support for renewable energy can take the form of financial incentives given to individuals or companies to deploy renewable energy. These include subsidies, production incentives, tax exemptions, grants and loans. A second category of policies contains regulations that mandate the power system to produce a certain quota of clean energy. Policy regimes can require an increasing percentage of the electricity that electric utilities sell to come from renewable energy sources by a specific date (e.g., Renewable Portfolio Standards) or offering green power options to consumers (e.g., Mandatory Green Power Option).

We borrow from the existing political economy theories in order to describe the possible behaviors of state governors in the area of renewable energy policy. Within each state government, the governor has substantial influence on the policy-making process. The role of the governor is central to determine the level of public support for renewable energy. Governors can target more (less) stringent renewable energy policies by increasing (lowering) the level of public support. Voters, on the other side, have heterogeneous preferences on renewable energy policies: they balance the benefits of clean energy (e.g., environmental quality) against the costs (e.g., fiscal burden of financing public support and subsidies, higher electricity prices).

Looking at policy outcomes, several combinations are possible depending on the assumptions we make about politicians' motivations. If politicians are solely office-motivated and not interested in policies, we should not expect to see differences in the stringency of renewable energy policy across governors from different parties. This is the main implication of the median voter theorem which states that politicians ultimately compete for the support of the median voter. Consistently with this theory, disparities in environmental policy stringency across states can be attributed to local factors as differences in the public opinion in each state (i.e., the sensitivity of the median voter towards the environment) rather than to the political orientation of the government.

Conversely, if politicians do not care only about holding office, but also about policy implementation, divergence of policy outcomes across different parties may occur after elections. A relaxation of the Downsonian paradigm conceives that politicians do not exclusively care about winning office, but they also have an incentive to implement the preferred policy if they are not fully committed to electoral platforms [Alesina (1988)]. Politicians may have heterogeneous motivations, while voters value some characteristics inherent to policy-motivated politicians [such as policy implementation efforts as proposed by Callander (2008) or the "character" as suggested by Kartik and Preston Mcafee (2007)]. In the event that policy-motivated politicians are "selected out" through electoral competition, it is possible that policy outcomes shift away from the the median voter's preference.

We draw from these theories and allow politicians to be partisan. We assume that governors may have or not a preference over climate policies. But if they do have one, it will coincide with the policy position of the party they are affiliated to. Policy-motivated candidates plausibly pursue their careers in a political party that better represents their personal policy preferences. In the case of the U.S., these are essentially two: the Democratic and the Republican party. Thus, policy divergence between Democrats and Republicans emerges if two conditions simultaneously hold. First, there are differences in policy preferences between the Democratic and the Republican parties. Second, governors are sufficiently policy-motivated to stick to their policy preferences after elections. Note that it is not sufficient to observe policy convergence to conclude that politicians do not have a preference: it may simply be the case that both the Democratic and Republican party share the same policy position.

In addition, we incorporate the role of lobbying by special interest groups in order to disentangle the truthful politicians' motivations. Instead of following their own partisan ideology or policy preference, politicians might deviate under circumstances that give them an incentive to do it. We argue that this is the case when they face the lobbying pressures by two groups: the opponents and supporters of renewable energy sources. Both groups are organized and lobby the governor through financial contributions [as in Grossman and Helpman (1994)] or by guaranteeing blocks of votes [as in Bombardini and Trebbi (2011)]. Governors value contributions by lobbies on their (or of their party) electoral support for future elections. Only if politicians are purely policy-motivated, we should not expect them to distort their preferred policy choices in response to lobbying pressures.

The group of opponents is constituted by the producers from the manufacturing industries. In this sector, energy is a large input for production. Profits therefore depend on the use of inexpensive electricity sourced from conventional polluting sources. Since these producers have much to lose from a climate policy that increases the electricity prices, they are expected to lobby governors in order to lower the level of public support for renewable energy sources.

The group of supporters comprises renewable energy producers. Renewable technologies produce energy from natural resources (e.g., wind speed or solar irradiation) without requiring additional inputs or efforts other than the maintenance of power plants. Profits depend on the quantity of energy that is produced and sold in the market. Rents also depend on the level of public support guaranteed to renewable energy production through direct or indirect subsidies, remunerative incentive schemes or regulation. Thus, at the same level of public support, the expected returns of investments in renewable energy projects are larger in those geographical areas where renewable natural resources are abundant. We expect that renewable energy producers lobby governors to choose higher levels of public support and that their lobbying activity will concentrate in those areas where they maximize profits (i.e., areas endowed by abundant renewable resource).

In short, we formulate the following hypothesis:

(i) hypothesizing that politicians belonging to the Democratic party care more about the environment and climate mitigation than Republicans, partisan motives drive differences in policy outcomes with Democratic governors more likely to support renewable energy;

(ii) even a governor with a policy attitude towards climate mitigation will support less (more) stringent renewable energy policies in presence of strong manufacturing interests (abundant renewable energy resources), unless she is purely policy-motivated.

In what follows, we empirically test these hypothesis. First, we estimate the effect of governors' party affiliation on renewable energy policy stringency and, second, we explore whether the effect is conditioned by holding office motives. In the next section we present the empirical methodology.

1.4 Empirical Methodology and Data

1.4.1 Empirical Strategy

The first purpose of our empirical strategy is to assess whether there are differences across Democratic and Republican governors in the stringency of renewable energy policies. Our focus is on estimating the effect of governors' party affiliation on renewable energy outcomes. The baseline estimating equation is the following:

$$Y_{it} = \alpha + \beta_1 D_{it} + \gamma' Z_{it} + \delta_i + \phi_t + \epsilon_{it} \tag{1.1}$$

where the dependent variable, Y_{it}, is our policy outcome variable: the installed renewable capacity (in log) in state i and year t. Our primary regressor is the treatment dummy variable D_{it} which equals to one whenever the current governor is Democrat, and zero if she is Republican. The coefficient β_1 in (1.1) captures the main effect of interest: the effect of governor party affiliation on the state level of renewable installed capacity. The vector Z_{it} contains the control variables as presented in the data section. A dummy for RPS adoption accounts for the presence of mandatory Renewable Portfolio Standard in force in state i and year t . Electricity use per capita, average end-use electricity price and carbon dioxide emissions per capita account for energy and environmental characteristics that are specific to each state. Socio-economic variables include state population, state real personal income per capita, percentage of the population over 65 and between 5 and 17. By exploiting the panel structure of our data, we include state fixed effects, δ_i, and time fixed effects, ϕ_t, in order to control for unobserved state characteristics and common time shocks, respectively. Finally, ϵ_{it} is the observation specific error.

In case we find evidence on different patterns in renewable energy between Democratic and Republican governors, the second purpose of the analysis is to explore whether governors deviate from their own political preference in response to the presence of political pressures by opponents and supporters of renewable energy sources. We test for potential heterogeneity effects of political party affiliation across states by interacting the political party dummy with terms accounting for lobby groups' political pressures. To do so, we extend our baseline specification (1.1) as follows:

$$Y_{it} = \alpha + \beta_1 D_{it} + \beta_2 D_{it} \times M_i + \beta_3 D_{it} \times E_i + \gamma' Z_{it} + \delta_i + \phi_t + \epsilon_{it} \qquad (1.2)$$

where M_i represents our proxy measure of lobbying against renewable energy policies. This variable is either indicated as GSP manufacturing share, employment manufacturing share, GSP share of "Energy-intense manufacturing industries" or employment share of "Energy-intense manufacturing industries". The proxy variable for the lobbying activity by pro-renewable supporters is expressed as E_i. The variable indicates the natural renewable endowment specific to each state: wind potential, solar potential or a combined indicator of both.

Both M_i and E_i are time-invariant variables and appear in equation (1.2) only interacted with our treatment variable D [13]. Given the fixed effects estimation, we cannot retrieve their direct (not interacted) effects. Regardless of this, our main focus is on exploring the possible sources of heterogeneity in governors' policy

[13] See the following sections or the Data Appendix for further information about M_i and E_i.

outcomes. Thus, we are interested in the interaction effects between the political party indicator and the proxies of lobbying political pressures (i.e., $\beta_1 + \beta_2$ and $\beta_1 + \beta_3$). As an additional investigation, we run regressions by considering the yearly time-variant measure of GSP manufacturing share. Natural endowment measures are otherwise only available as time-invariant.

Our identification strategy relies on the use of exogenous proxies for lobbying pressures. We exploit the exogenous variation of the interaction terms across states in order to assess if the effect of belonging to the Democratic party (as opposed to the Republican) varies with them. For what concerns the natural renewable endowment, the use of wind and solar potential does not raise serious endogeneity concerns. In fact, these measures have the advantage of being fully exogenous in the empirical specification since they strictly depend on geographical and climate characteristics of each state. On the contrary, measures of the share of manufacturing GSP and employment might suffer from endogeneity issues, especially because of reverse causality with the dependent variable. To address this problem, we employ time-invariant variables calculated as averages over the four years (1990-1994) preceding the time window of our panel. This helps to attenuate the bias in our estimated coefficients due to the concurrent effects of clean energy transition on the economic sectors. Including a full set of control variables and fixed effects also contribute to limit omitted variable bias. In addition, both M_i and E_i are continuous variables. Thus, we do not have to worry about sensitivity issues due to the use of discrete indicators and state classifications or to sample splitting by arbitrary cutoff points.

In all empirical specifications, we use robust standard errors clustered at state-electoral term pairs. This choice accounts for the fact that our treatment variable is at the gubernatorial term and not at the state level. Clustering standard errors by state-electoral term pairs correctly reflects the treatment assignment mechanism of Democratic governors' terms. In addition, Cameron et al. (2006) and Abadie et al. (2017) inform that clustering at the most aggregate level when there are "few" clusters can lead to complications to statistical inference [14]. Complications are typically such that adjusted standard errors are unnecessarily conservative, t-statistics tend to over-reject and confidence intervals are too narrow[15].

[14] The rule of thumb is that clustering standard errors is likely to lead to over-rejection when the number of clusters is below 50. In our case, since we have 48 states, if we cluster at the most aggregate level (i.e., the state level) we might have unnecessarily too conservative results.

[15] As robustness check, we run the previous regressions with robust standard errors clustered at the state level. The significance of the results does not substantially drop, even though standard errors are larger. These results are available upon request.

1.4.2 Renewable Energy Outcome

As a proxy measure of renewable energy policy stringency, we use the installed capacity (in MW) from renewable energy sources excluding hydropower (see the Data Appendix for more details). The data is sourced from the U.S. Energy Information Administration (EIA). Installed capacity is an outcome variable of renewable energy policies, but it is not a direct policy indicator. Unfortunately, a comprehensive policy indicator that quantifies the extent of renewable energy policies does not exist. It can hardly be calculated over time given the complexity and diversity of state public support schemes. Thus, given the centrality of public support in renewable energy deployment, we exploit outcome variables that are directly correlated with the policy objectives. We also prefer to use the data on the installed capacity instead of net electricity generation (in MW/hours). First, installed capacity does not fluctuate with temporary exogenous shocks in the supply or in demand of electricity. It is also less geographically/climate sensitive than electricity generation. Second, installed capacity better reflects the investment undertaken in renewable energy technologies and, thus, it is highly correlated with the policy tool driving it. Finally, we extend our baseline empirical specification using as dependent variables the installed capacity of hydroelectric, nuclear and fossil fuel (i.e., coal, natural gas and oil) energy production as a “placebo test” in order inspect further the validity of our results.

1.4.3 The Manufacturing Sector and Natural Endowment

We have previously hypothesized that producers from manufacturing industries will likely oppose public support for renewable energy as it negatively impacts on their profits by raising the costs of energy. To proxy the relative political pressures by this lobby group, we employ the share of the manufacturing sector of total Gross State Product (GSP) and, alternatively, the manufacturing employment share of total population [16]. In addition, we build other two more specific indicators of GSP manufacturing and employment by selecting only energy-intensive industries, which are the most affected by renewable energy policies (see Data Appendix for further details). The data are sourced from the Bureau of Economic Analysis (BEA).

While GSP manufacturing and employment shares have the advantage of being available at the state level, they have the drawback of not directly linking the lobbying activity with the policy issue at stake. Even though we are aware that

[16]Manufacturing employment is calculated as the fraction of total state population.

they only approximate the lobbying contributions anti-renewable energy, their use is supported by the existing research [17]. In the Data Appendix, we provide preliminary evidence on the correlation between electricity prices, renewable electricity generation and state GSP manufacturing shares, supporting the use of these proxy variables. Nevertheless, GSP manufacturing and employment emphasize different aspects. Larger industry sector's contribution to the economy indicates a greater economic interest at stake and, thus, larger lobbying contributions through which the lobby group influences the policy outcome. [18] Otherwise, if the share of workers employed in the industry sector is relatively large, lobby group influence can be exerted by directly ensuring electoral support and votes of the employers (i.e., even without devoting lobbying contributions) [Bombardini and Trebbi (2011)].

To proxy the political influence of the interest group supporting renewable energy policies, we exploit the exogenous variation in the presence of renewable energy resources across the U.S. states. As previously discussed, we argue that the interests of pro-renewables supporters concentrate where it is more profitable to produce renewable electricity (i.e., in geographical areas abundant of renewable energy resources). Our measures of renewable resource endowment are wind and solar potential (see for further details the Data Appendix). In addition, we construct a combined indicator (in log and normalized to zero) of natural renewable endowment by multiplying wind and solar potential. The data are sourced from the National Renewable Energy Laboratory.

Even in this case, we are aware that these measures are only proxies of the potential underlying lobbying dynamics. However, it is widely supported by the literature that natural endowment is a key element for the economic viability of renewable energy transition. The development of renewable energy industries naturally depends on the presence of renewable resources such as wind and solar potential that are specific to a particular geographical location and cannot be moved across territories [Menz and Vachon (2006); Carley (2009); Delmas and

[17]Fredriksson et al. (2004) provides evidence that industries belonging to the manufacturing sector are relatively more energy intensive than other sectors such as commercial, services and construction. Greenstone and Nath (2019) points out that manufacturers are the most exposed group in the economy to the negative impacts of renewable energy programs that increase the electricity prices. Moreover, evidence on industrialized countries suggests that the presence of strong manufacturing interests effectively hindered the penetration of renewable energy sources [Aklin and Urpelainen (2013) Cadoret and Padovano (2016)].

[18]We do not consider coordination problems. Fredriksson and Millimet (2004), instead, argue that the effect of industry sector size is ambiguous since interest groups larger in size have also larger coordination costs (i.e., due to the fact that a large industry usually comprises a large number of firms).

Montes-Sancho (2011)]. Gennaioli and Tavoni (2016) provide evidence that higher levels of natural renewable endowment can attract the interests of clean energy producers. On one side, the natural context plays a major role for the establishment of "green" energy corporations and constituencies, and on the other side it makes it easier for policy-makers to introduce and preserve renewable energy policies.

1.4.4 Other Variables

Our key explanatory variable is a dummy treatment variable which is equal to one if the current governor in a given state-year belongs to the Democratic party, and zero if she belongs to the Republican party. The data are retrieved from Dave Leip 's Atlas of U.S. Elections [19].

The set of control variables includes regulatory, energy and environmental variables related to each state. These controls are widely used in the literature on renewable energy sources, for example by Carley (2009), Delmas and Montes-Sancho (2011) and Cadoret and Padovano (2016). A dummy variable is equal to one if the state had a Renewable Portfolio Standard (RPS) in place and zero otherwise. It accounts for the effect of this widely used policy regime on the level of renewable energy capacity. The indicator is compiled from the Lawrence Berkeley National Laboratory excluding any voluntary RPS programs. The variable *state electricity use per capita* (MWh per person) represents the total electricity demand of each state. It is calculated as the total annual amount of net electricity generation divided by the associated state population. We include the *average annual retail price of electricity* (in cents/kWh) as the average price available across all end-users (i.e., residential, commercial, industrial and transportation). Finally, state energy-related *carbon dioxide emissions per capita* (in millions of metric tons of CO2 per person) represent an approximative measure of the environmental degradation specific to each state. The previous three variables come from the U.S. Energy Information Administration (EIA) and capture state characteristics related to the energy market that can motivate different state-specific trends. In addition, we include control variables accounting for socio-economic

[19]Since we are interested in estimating the effect of party affiliation to the two main political groups (Democrats and Republicans) we exclude elected governors from other political parties. We also want to focus on the behavior of politicians that are directly accountable to voters through a competitive electoral process. We therefore do not consider lieutenant governors or politicians standing in office in the event of death, resignation or removal of the incumbent governor without a recall gubernatorial election. In any case, these two exclusion criteria involve a very small number of observations and do not affect our sample size.

characteristics of each state: *state population, state real personal income per capita, percentage of the population over 65* and *percentage of the population between 5 and 17.* These controls are also found in List and Sturm (2006) and Fredriksson et al. (2011) and allow for a better comparison with the results from the previous political economy literature. Data on state population and personal income come from the US Bureau of Economic Analysis (BEA). Data on the percentage of the aged and young population are from the US Census Bureau database.

1.4.5 Final Sample

We perform the main empirical analysis using a panel dataset for the period 1995-2010 with annual observations on 48 U.S. states [20]. Table 1.1 provides summary statistics of all variables employed.

The sample consists of 704 state-year observations [21]. We express in natural logarithms all arguments of the dependent (i.e., installed capacity) and independent variables (i.e., wind and solar potential, state electricity use per capita, electricity price, carbon dioxide emissions per capita, real income per capita, population). The only variables not transformed are those defined in shares and percentages (i.e., GSP manufacturing shares, manufacturing employment share, percentages of aged and young population). Our analysis focuses on period from 1995 to 2010 which corresponds to the initial phase of renewable energy deployment. During this period renewable technologies were far from competitive with conventional sources and they needed important public support in order to develop in the market. It is therefore an ideal time window to study the political-economy drivers of their development. In the robustness check section, we extend our dataset until 2018 and we discuss the advantages and drawbacks of including the most recent years in the econometric analysis.

[20] As common in the literature using U.S. state data, we do not include Alaska and Hawaii given their exceptional geographical-climate location and their dependence on federal funds.

[21] The number of observations is lower than all the state-years combinations (i.e., 768) for two reasons. First, as previously explained, we are focusing on the competition between Democrats and Republicans and we are not considering states ruled by governors from third parties (i.e., 16 state-years observations in our sample). Second, by using a logarithmic transformation of the dependent variable, we drop the pairs with zero values in installed capacity (i.e., 48 state-years observations for renewable installed capacity). In the robustness check section, we address this limitation by employing alternative empirical specifications that deal with zero values without simply dropping them.

Tab. 1.1: Summary Statistics.

	Mean	SD	Min.	Max.	Obs.
ln (Renew. Capacity)	5.27	1.66	-1.83	9.24	704
ln (Hydro Capacity)	6.19	1.8	.693	9.95	683
ln (Fossil Capacity)	9.17	1.21	4.91	11.5	704
ln (Nuclear Capacity)	7.88	.788	6.33	9.53	467
Democrat	.432	.496	0	1	704
GSP Manufact.% (Time-inv.)	0	6.44	-13.9	12.1	704
GSP Manufact.% (Time-var.)	0	5.83	-10.9	16.4	704
Employment Manu. % (Time-inv.)	0	2.59	-5.1	5.13	704
GSP Energy-int. Manu.% (Time-inv.)	0	1.45	-2.51	3.2	704
Empl. Energy-int. Manu.% (Time-inv.)	0	.511	-.834	1.31	704
Wind potential (Time-inv.)	0	1.67	-3.76	3.14	704
Solar potential (Time-inv.)	0	.117	-.293	.291	704
Ren. Endowment (Time-inv.)	0	1.68	-3.82	3.28	704
RPS	.327	.469	0	1	704
ln(Electricity use per capita)	2.67	.527	1.48	4.53	704
ln(Electricity Price)	2	.305	1.35	2.89	704
ln(CO2 emissions per capita)	3.03	.521	2.18	4.86	704
ln(Population)	15.2	.979	13.1	17.4	704
ln(Real personal income per capita)	9.74	.159	9.35	10.3	704
Population over 65%	12.8	1.63	8.5	18.6	704
Population between 5 and 17%	18.2	1.35	15	24.8	704

Notes: The sample time span is from 1995 to 2010. Data on installed capacity for renewables, hydropower, fossil fuels and nuclear are sourced from the U.S. Energy Information Administration. Data on governors' political parties are taken from Dave Leip's Atlas of U.S. Elections. Data on Gross State Product (GSP), GSP manufacturing sector, GSP energy-intensive industries and relative employment levels are sourced from the Bureau of Economic Analysis. Data on wind and solar renewable endowment are from the National Renewable Energy Laboratory. Information about state Renewable Portfolio Standards are compiled from the Lawrence Berkeley National Laboratory. Data on electricity use, electricity prices, CO2 emissions come from the U.S. Energy Information Administration. Data on state population and personal income are from the Bureau of Economic Analysis. Data on state age characteristics are from the Census Bureau.

1.5 Results

Table 1.2 reports results of estimating equation (1.1) (i.e., without interactions) and equation (1.2) (i.e., with interaction terms of lobbying proxies). Our main explanatory variable of interest is a political party dummy equal to 1 for Democratic governors (treatment effect) and to 0 for Republican governors. In column (1), we first estimate the average governor's party affiliation effect on the state level of renewable installed capacity (in log). In column (2) and (3) we report

Tab. 1.2: Renewable Capacity, Governor's Party Affiliation and Interactions, 1995-2010.

	Dependent Variable: ln (Renew. Capacity)			
	(1)	(2)	(3)	(4)
Democrat	0.391***	0.430***	0.390***	0.431***
	(0.147)	(0.140)	(0.148)	(0.142)
Democrat × GSP Manufact.% (Time-inv.)		-0.0514**		-0.0542**
		(0.0212)		(0.0217)
Democrat × Ren. Endowment (Time-inv.)			0.199**	0.214**
			(0.0990)	(0.103)
RPS	0.387**	0.390**	0.356**	0.356**
	(0.179)	(0.175)	(0.179)	(0.177)
ln(Electricity use per capita)	-0.691	-0.545	-0.785	-0.639
	(0.516)	(0.500)	(0.494)	(0.474)
ln(Electricity Price)	-1.667***	-1.581***	-1.614***	-1.518***
	(0.556)	(0.565)	(0.534)	(0.537)
ln(CO2 emissions per capita)	3.704***	3.578***	3.558***	3.414***
	(1.137)	(1.140)	(1.148)	(1.159)
ln(Population)	6.239***	6.538***	5.835***	6.121***
	(1.704)	(1.605)	(1.753)	(1.665)
ln(Real personal income per capita)	2.311	1.160	2.374	1.164
	(1.592)	(1.579)	(1.574)	(1.554)
Population over 65%	-0.277	-0.367**	-0.315	-0.412**
	(0.194)	(0.185)	(0.195)	(0.183)
Population between 5 and 17%	-0.502***	-0.503***	-0.450***	-0.446***
	(0.115)	(0.118)	(0.112)	(0.116)
State F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Observations	704	704	704	704
R2	0.816	0.822	0.820	0.827

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The Table shows OLS regression results of estimating equation (1.1) and equation (1.2). Column (1) reports results from the baseline empirical specification which concerns the relationship between renewable installed capacity and political party affiliation with no interactions. Column (2) and column (3) report the results from interacting the political dummy indicator with GSP manufacturing share and combined natural renewable endowment, respectively. Standard errors (in parentheses) are clustered at state-electoral term level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

results of interacting our treatment D with linear terms of (time-invariant) GSP manufacturing share and (time-invariant) combined renewable endowment (in log), respectively. Column (4) includes both interactions term. All estimations include the following controls: a dummy indicator equal to 1 if the state has a Renewable Portfolio Standard in force, electricity use per capita (in log), average end-use electricity price (in log), carbon-dioxide emissions per capita (in log), state population (in log), real personal income per capita (in log), share of population older than 65, share of population younger than 17. All the specifications include state fixed and time effects. The results remain stable even if we remove the control variables from the estimation. Since all arguments of the variables are expressed in natural logarithms (with the exception of share variables), we can interpret the coefficients as elasticities and semi-elasticities.

The relevant coefficient β_1, from equation (1.1) is always positive and significant at conventional levels across different specifications. The coefficient remains stable after including the interaction terms. The magnitude ranges between 0.391 and 0.431. This suggests that renewable capacity increased about 48% and 54% [22] under Democratic governors as compared to Republican ones [23].

However, there is evidence of heterogeneity effects of governor's party affiliation across states. In column (2), the coefficient β_2 on the interaction term with the GSP manufacturing share is negative and significant. The party affiliation effect is decreasing with larger levels of GSP manufacturing share. The opposite pattern is observed in column (3) when we interact our treatment variable D with renewable endowment (in log). The coefficient β_3 is positive and significant. The effect of Democratic governors becomes bigger with better renewable endowment. The coefficients remain stable in column (4) after including both interaction terms. This is our preferred specification since it incorporates both proxy measures of the political influence against and in favor renewable energy deployment, respectively. For instance, as GSP manufacturing is raised by 1% relative to the average, the difference in renewable energy outcomes between Democrats and Republicans shrinks by about 8% [24]. Instead, as the endowment increases by 10%, the effect of Democratic party affiliation is about 3% percentage higher than the average effect [25].

Model (4) suggests that Democratic governors promote more renewable energy than the Republican counterparts only under specific circumstances which depend on state characteristics. Figure 1.1 plots the marginal effect of Democratic party affiliation for different levels of GSP manufacturing shares (panel a) and for different levels of renewable endowment (in log) (panel b). The figure graphically shows that the difference in renewable capacity between Democratic and Republican governors becomes smaller (and not significant) in those states

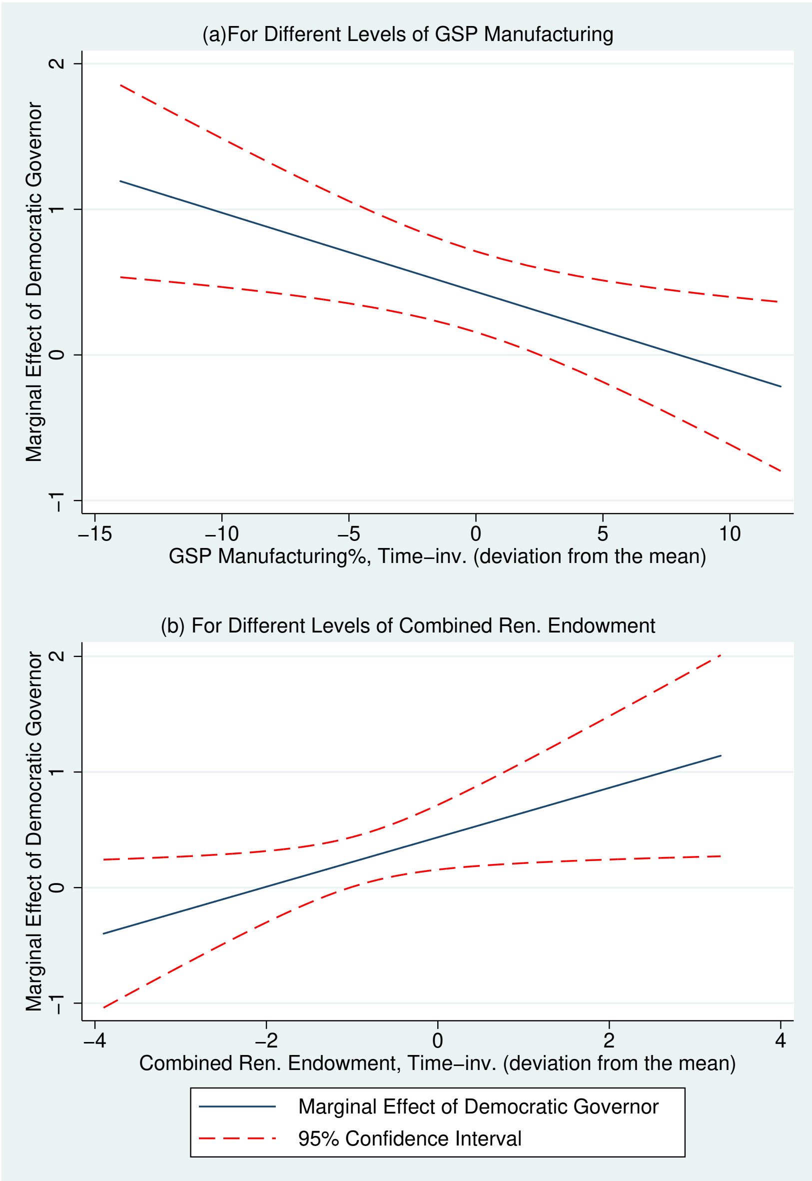
[22] We used the following relation to compute the economic effect: $(e^{\beta} - 1) \times 100\%$ where β is the estimated coefficient.

[23] The effect of Democratic party affiliation that has been estimated seems to be economically large but it needs to be evaluated in relation to the exponential annual growth rates characterizing renewable energy deployment.

[24] From $(e^{\beta_1} - 1) \times 100 = (e^{0.431} - 1) \times 100 \approx 54\%$ and $(e^{\beta_1 - \beta_2} - 1) \times 100 = (e^{0.431-0.0542} - 1) \times 100 \approx 46\%$.

[25] From $(e^{\beta_1 + \beta_3} - 1) \times 100 = e^{(0.431+0.214\times\ln(1.1))} - 1) \times 100 \approx 57\%$.

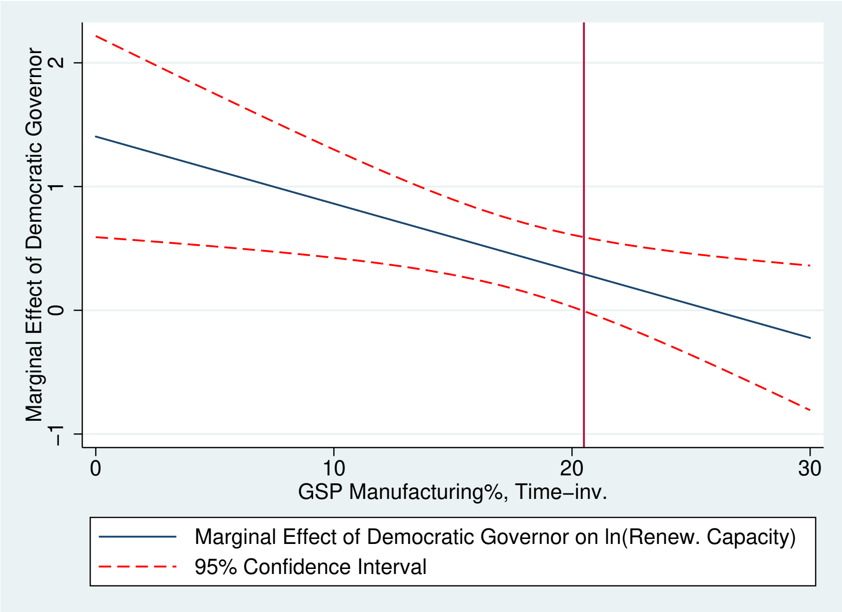
Fig. 1.1: Heterogeneous Effect of Party Affiliation on Renewable Capacity



Notes: The figure plots the marginal effect of Democratic party affiliation on state renewable installed capacity (excluding hydropower). Point estimates are derived from estimating equation (1.2) using the GSP manufacturing share and the combined renewable endowment as interaction terms. All the control variables described in the data section are included in the estimation.

with a large share of GSP manufacturing. Meanwhile, the difference becomes bigger (and significant) for a sufficiently large level of natural renewable endowment. These results suggest that effect of party affiliation is not relevant in magnitude and is not statistically significant for those states where the manufacturing industry is relevant or the endowment of natural renewable resources is scarce. For instance, our estimates suggests that there are no differences in renewable energy outcomes across governors from different parties in states where the share of GSP

Fig. 1.2: Heterogeneous Effect of Party Affiliation on Renewable Capacity (continued)



Notes: Point estimates are derived from estimating equation (1.2). GSP Manufacturing share is not normalized to zero but it is kept in the original form. All the control variables described in the data section are included in the estimation.

manufacturing exceeds the value around 20% (Figure 1.2). [26] In Table 1.3 we present the results from regressing equation (1.2) using alternative proxy measures of lobbying. In columns (1), we interact the Democratic dummy with an alternative measure of the group size that is expected to lobby against renewable energy policies, i.e., the manufacturing employment share of total population. The variable is time-invariant and, similarly to what we do for GSP manufacturing share, it is calculated as average over 1990 - 1994 in order to address potential endogeneity. Some authors have suggested that there exists a substitution effect between two channels of lobby groups' influence, i.e., financial contributions and their own voter representation [Bombardini and Trebbi (2011)].

[26] In this figure we do not express GSP manufacturing share as devation from the mean, but in the original form.

Tab. 1.3: Results using other interaction terms

	Dependent Variable: ln (Renew. Capacity)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Democrat	0.413***	0.466***	0.448***	0.393***	0.430***	0.395***	0.353**	0.357**
	(0.142)	(0.144)	(0.143)	(0.148)	(0.139)	(0.150)	(0.138)	(0.140)
Democrat × Employment Manu.% (Time-inv.)	-0.182***							
	(0.0514)							
Democrat × GSP Energy-int. Manu.% (Time-inv.)		-0.344***						
		(0.0886)						
Democrat × Empl. Energy-int. Manu.% (Time-inv.)			-0.890***					
			(0.237)					
GSP Manufact.% (Time-var.)				0.00621	0.0340			
				(0.0336)	(0.0303)			
Democrat × GSP Manufact.% (Time-var.)					-0.0640***			
					(0.0243)			
Democrat × Wind Potential						0.171*		0.164*
						(0.0984)		(0.0947)
Democrat × Solar Potential							4.394***	4.355***
							(1.159)	(1.148)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	704	704	704	704	704	704	704	704
R2	0.827	0.829	0.827	0.816	0.824	0.819	0.830	0.833

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Empirical specifications by interacting Democratic governor dummy with alternative terms: employment manufacturing share (column 1), GSP and employment share from energy-intensive industries (column 2 and 3), GSP manufacturing share (Time variant) (column 4 and 5), wind and solar endowments (column 6, 7 and 8). All the control variables described in the data section are included. Standard errors (in parentheses) are clustered at state-electoral term level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

Our results contribute to their findings by showing that the effect of manufacturing lobbying is particularly strong when the industry size is large in term of workers/employers. In fact, the coefficient on the interaction term with the manufacturing employment share (time-invariant, mean over 1990 - 1994) is more than three times higher in magnitude (-0.182) than the interaction coefficient with GSP manufacturing share (-0.0514). The voting representative population of the manufacturing sector seems to significantly influence governors's decisions, even more than what we could expect by simply looking at the sector's contribution to the state's economy.

In columns (2) and (3), we use as interaction terms the GSP and employment shares of energy-intensive manufacturing industries, respectively. Both variables are time-invariant (mean over 1990-1994). Instead of considering the manufacturing sector as a whole, these variables are more specific proxy measures of anti-renewable lobbying pressures, They are obtained by selecting and aggregating the most energy intensive industries belonging to the manufacturing sector, as suggested by Fredriksson et al. (2004) [27]. The coefficients estimated for the interaction terms are by far larger in magnitude than those those obtained by interacting our treatment D with GSP and employment manufacturing share, respectively. This seems to suggest that the heterogeneity effects of governors' party affiliation are mainly driven by the political pressures coming from energy-intensive industries. It can be possibly explained by the fact that energy-intensive industries are the most penalized by renewable energy policies that increase electricity prices and, therefore, have the largest interest at stake in the policy-making.

Columns (4) and (5) of Table 1.3 add to the specification the yearly time variant measure of GSP manufacturing share. This allows us to study its direct effect on renewable installed capacity, i.e., not only the interaction effect with the political party dummy. [28]. The coefficient on (time variant) GSP manufacturing share is not significantly different from zero. The coefficient on the interaction with the party dummy is similar to the one obtained by employing the time invariant measure of GSP manufacturing share in Table 1.2. This gives more robustness to our previous results. However, it is important to note that including this time-variant measure raises endogeneity concerns. In fact, reverse causality may be an issue since renewable energy deployment is likely to affect also the size and composition of manufacturing industries.

[27] Energy intensive industries are primary metal manufacturing, nonmetallic mineral manufacturing, paper, printing and publishing.

[28] By using a state fixed-effects models and time-invariant state specific variables, we can only study their interactions with other time varying covariates.

In columns (6), (7) and (8), we disentangle the single effect of interacting our treatment variable (i.e., D) with wind or solar potential. In fact, combining the two measures into a single variable may raise potentially two concerns. First, the variable is calculated by multiplying two indicators of renewable energy potential that are expressed with different units of measure. Second, an aggregated variable does not allow to evaluate the single contributions of the two renewable endowments. The results in column (8) of Table 1.3 indicate that, even if both effects are positive, the coefficient on the interaction effect with solar potential is larger in magnitude and more significant than the interaction coefficient with wind potential. This suggests that heterogeneity in the party affiliation effect is mainly driven by the variation in state solar resources rather than in wind potential. Summarizing, results from Table 1.2 and Table 1.3 show that there exist some degree of partisan divergence in renewable energy outcomes. Democratic governors achieved higher levels of renewable installed capacity during their terms as opposed to Republicans. However, we find important heterogeneity in the effect. In states where the manufacturing industry is strong, even governors whose ideology is driven towards the environment do not promote more renewable energy. Instead, Democratic governors are more willing to promote renewable energy sources whenever renewables supporters have a high interest at stake, i.e., in states abundant of renewable endowment. These results seem to be consistent with those found by Fredriksson et al. (2011). Even if we find, at first, differences in renewable energy outcomes between the Democratic and the Republican parties, the effect highly depends on state characteristics which suggest that other political-economy dynamics are in action. Our results show that politicians deviate from their preferred policy choice in response to the presence of strong interests of opponents and supporters of renewable energy. This is in contradiction with what we should expect if politicians are purely policy-motivated. Indeed, partisan ideology is overridden whenever there are strong holding office incentives. Interestingly, we find evidence that Democratic politicians are subjected to anti-environmental lobbying pressures that essentially hinder renewable energy penetration. This suggest that the anti-environmental lobby group do not only support Republican candidates to vote against the environment (as suggested by the literature), but also influence policy choices of Democratic affiliates.

1.6 Robustness Check

In this section, we assess the robustness of our results. In Table 1.4 we report results from a "placebo" test performed by replacing the dependent variable of our baseline specifications (i.e., renewable installed capacity, excluding hydroelectricity) with the installed capacity of the following technologies: hydroelectric, fossil fuels and nuclear, respectively. By doing so, we want to test whether our treatment (i.e., Democratic party affiliation) have a technology-based effect or not. If our treatment had a common impact across all technologies, we could not attribute the increase in renewable energy capacity to a specific commitment of governors in clean energy transition. The increase would be rather associated with other confounding events or policies that are not technology-specific but have an impact on the total level of installed capacity. Our arguments and results would be undermined even if we find a common pattern with technologies that does not need public support or specific "green" regulation. The placebo test excludes that our treatment variable had a significant impact on hydroelectric power capacity [column (1)] and on fossil fuel capacity [column(2)]. Note that hydropower is a renewable energy source, but it was developed in the market

Tab. 1.4: Placebo Test: Regressions with other Dependent Variables.

	ln (Hydro Capacity) (1)	ln (Fossil Capacity) (2)	ln (Nuclear Capacity) (3)
Democrat	0.00607	0.00604	0.00900*
	(0.0146)	(0.0154)	(0.00484)
Democrat × GSP Manufact.% (Time-inv.)	-0.0000724	-0.0000185	0.000715
	(0.00157)	(0.00259)	(0.000743)
Democrat × Ren. Endowment (Time-inv.)	-0.00580	-0.0114	-0.00275
	(0.0102)	(0.0105)	(0.00288)
Controls	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	720	752	488
R2	0.998	0.991	0.998

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Placebo tests are performed by replacing the dependent variable with: installed capacity for hydropower (column 1), installed capacity for fossil fuels (gas, oil and coal) (column 2) and installed capacity for nuclear (column 3). All the control variables described in the data section are included. Standard errors (in parentheses) are clustered at state-electoral term level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

Tab. 1.5: Results using different empirical specifications

	OLS estimations Dep. Variable: ln(Renew. Capacity + 1)				PPML estimations Dep. Variable: Renew. Capacity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Democrat	0.366**	0.405***	0.360**	0.399***	0.469***	0.427***	0.468***	0.423***
	(0.151)	(0.148)	(0.152)	(0.148)	(0.113)	(0.110)	(0.113)	(0.111)
Democrat × GSP Manufact.% (Time-inv.)		-0.0585***		-0.0600***		-0.0439**		-0.0458**
		(0.0223)		(0.0227)		(0.0206)		(0.0216)
Democrat × Ren. Endowment (Time-inv.)			0.123	0.135			0.146**	0.154**
			(0.116)	(0.117)			(0.0661)	(0.0636)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	752	752	752	752	752	752	752	752
R2	0.831	0.836	0.832	0.837				
Pseudo R2					0.890	0.893	0.892	0.895

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robustness checks by replacing the Dependent variable with ln(renewable installed capacity + 1) in columns from 1 to 4. In columns from 5 to 8, Poisson Pseudo Maximum Likelihood estimation using installed renewable capacity (not in logs) as dependent variable. Interactions terms are GSP manufacturing share and combined natural renewable endowment. All the control variables described in the data section are included. See the text or notes in table 1 for data description and sources. Standard errors (in parentheses) are clustered at state-electoral term level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

long before than modern renewables and its existing capacity has been saturated depending on geographical characteristics. The coefficient of party affiliation on nuclear capacity is significant at 10% but very small as compared to the coefficient on renewable capacity. The evidence suggests that, under Democratic governors, only renewable installed capacity increased significantly. This suggests that Democratic governors implemented specific policies targeting "non mature" clean technologies and gives robustness to our identification strategy [29].

We next experiment with empirical specifications that allow us to deal with zero values in renewable installed capacity. In fact, we lose about 6% of our sample observations when we log-transform the dependent variable. In Table 1.5 we report results for two different empirical specifications that can account for this sample selection bias. In columns from (1) to (4), we present the results obtained by substituting $\ln(Renew.Capacity + 1)$ as dependent variable in our baseline equations. The coefficients estimated do not significantly differ from our estimates in Table 1.2. The only exception is the coefficient on the interaction of

[29] We also tried using as dependent variable a relative (i.e., instead of absolute) measure of renewable energy deployment: the share of renewable installed capacity (excluding hydropower) of total installed capacity. Even using this variable improves the identification strategy. It avoids to confound common effects to all technologies with specific effects related to renewable energy deployment. In fact, this ratio measure the substitution of conventional sources with renewable energy sources and it directly captures clean energy transition without needing additional tests. Results remain substantially unchanged. These results are available upon request.

the party dummy with renewable endowment that is not significant anymore.

In columns from (5) to (8), we report results obtained by employing a Poisson Pseudo Maximum Likelihood estimator (PPML), as suggested by Silva and Tenreyro (2006). They argue that using log-linearized OLS under heteroskedasticy not only does not naturally deal with zero values but it also might lead to inconsistent estimates of the parameters. Using a PPML estimation, the dependent variable is expressed in levels and not in logs. The coefficients do not change significantly from those estimated in our baseline specification. The coefficient on Democrat is even larger in magnitude than the one reported in Table 1.2.

Finally, we run our main estimations extending the considered period to 2018, according to data availability. The results are presented in Table 1.6. As shown in the table, the Democrat coefficient is positive but not significant in any specifications considered. The interaction term between the treatment variable D (i.e., Democratic party affiliation) and the proxy for renewable energy supporters (i.e., combined renewable endowment) is positive but not significant, as shown in columns (3) and (4) [even for wind and solar potential when interacted separately in columns (8) and (9)]. The only coefficients that remain robust in the extended panel are the interaction terms between D and the proxies of anti-renewables lobbying: the time-invariant measures of GSP manufacturing share [column (2)], the GSP share of "Energy-intensive manufacturing industries" [column (5)], the employment manufacturing share [column (6)] and the employment share of "Energy-intensive industries" [column (7)]. These coefficient are negative and with a similar magnitude of those presented in Table 1.2 and Table 1.3. Thus, contrarily to Democrat party affiliation, the effect of anti-renewable lobby activity proves to be significant after extending the dataset.

The evidence shows that, after extending the panel, there are no differences in renewable energy outcomes between Democratic and Republican governors. However, including recent years presents potential drawbacks in relation to the scopes of our research. Indeed, there are several explanations for the time heterogeneity in our results. First, in 2009 the Obama Administration enacted the American Recovery and Reinvestment Act as a response to the economic crisis [30]. Since the package contains explicit policies for renewable energy, there is an overlapping of state-level policies with federal programs after its introduction. Thus, it becomes more difficult to disentangle the effects of state-level political

[30] The package has explicit objectives in energy efficiency, renewable energy research and investments. It constitutes the largest federal commitment for renewable energy sources since loans and investments into renewable energy technologies are a significant part of the final provisions of the act.

factors (i.e., the role of gubernatorial politics) from federal incentives.

Second, during the past decade renewable technologies have become more competitive in the energy market. Between 2010 and 2018, the levelised cost of electricity (LCOE) [31] of renewable power plants has fallen into the fossil-fuel cost range [IRENA (2019)]. This was mainly due to the technological progress and the drops in costs for components (wind turbines and solar panels) as the European Union and Asian countries started heavily investing in renewable energy. Thus, renewable energy sources have become more "mature" technologies and less dependent on policy regimes that subsidize their deployment. Due to this trend, it becomes even more difficult to decompose the political determinants from the market forces of clean energy transition when we include in the empirical analysis recent years.

The fact that the presence of renewable energy resources does not induce anymore heterogeneity in the the party affiliation effect is also related to technical progress. It plausibly indicates that, since greater efficiency compensates natural potential, the endowment of renewable resources might no longer be driving investment decisions in renewable energy. Instead, our results suggest that the presence of strong manufacturing interests continued to restrain, even until recent years, renewable energy penetration in states ruled by Democratic governors. Regardless the level of political polarization, lobbying pressures from the manufacturing sector continue having a relevant influence in weakening the scope of renewable energy policies.

[31] The LCOE of a given technology is the ratio of lifetime costs to lifetime electricity generation. LCOE from bioenergy, geothermal and wind have all been within the range of fossil fuel-fired power generation costs since 2010. Since 2014, the LCOE of solar photovoltaic has also become similar to fossil fuel generation costs [IRENA (2019)].

TAB. 1.6: Renewable Capacity, Governor's Party Affiliation and Interactions, Extended panel: 1995-2018.

	Time period: 1995 - 2018 Dependent Variable: ln (Renew. Capacity)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Democrat	0.0312	0.0674	0.0339	0.0696	0.0751	0.0700	0.0923	0.0331	0.0432
	(0.113)	(0.110)	(0.114)	(0.112)	(0.114)	(0.112)	(0.116)	(0.114)	(0.113)
Democrat × GSP Manufact.% (Time-inv.)		-0.0446**		-0.0443**					
		(0.0177)		(0.0179)					
Democrat × Ren. Endowment (Time-inv.)			0.0544	0.0493					
			(0.0676)	(0.0679)					
Democrat × GSP Energy-int. Manu.% (Time-inv.)					-0.207**				
					(0.0857)				
Democrat × Employment Manu.% (Time-inv.)						-0.126***			
						(0.0458)			
Democrat × Empl. Energy-int. Manu.% (Time-inv.)							-0.593**		
							(0.229)		
Democrat × Wind Potential								0.0446	
								(0.0678)	
Democrat × Solar Potential									2.033
									(1.287)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1075	1075	1075	1075	1075	1075	1075	1075	1075
R2	0.782	0.786	0.782	0.786	0.787	0.787	0.787	0.782	0.785

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Estimation of equation (1.2) using an extended time period from 1995 to 2018. All the control variables described in the data section are included. See the text or notes in table 1 for data description and sources. Standard errors (in parentheses) are clustered at state-electoral level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

1.7 Conclusion and Policy Implications

To the best of our knowledge, our study is the first empirical attempt that, based on a political economy approach, focuses on politicians partisanship, lobbying activity and their interactions to explain differences in renewable energy outcomes across the U.S. states. While the evidence on global warming has intensified the political competition on climate policies, we argue that politicians' choices over renewable energy policies depend both on policy preferences and on the political pressures by lobby groups that influence (positively or negatively) the scopes of climate policies. The U.S. federal setting constitutes an ideal testing ground given the substantial autonomy of state governments in environmental policy. We first investigate to what extent the party affiliation of governors, who have a prominent power in the policy formation process of each state, had an impact on state renewable energy achievements. The outcome variable is the state installed capacity from renewable power plants excluding hydropower. The focus is therefore on "non mature" renewable technologies that need public support schemes and regulations to develop in the market. Secondly, we investigate whether the party affiliation effect is conditioned on lobbying pressures. Empirically, we do so by interacting party affiliation with proxies of the strength of the two lobbying groups that oppose and support public intervention for renewables, respectively. The first set of proxies are measures of the state manufacturing industry size, while the second one measures the renewable energy state potential (which captures the profitability of renewable energy investments).

We find evidence revealing that during the initial phase of renewable energy deployment governor's affiliation to the Democratic party had on average a positive impact on the state level of renewable capacity. However, the effect is highly heterogeneous. No differences in renewable energy outcomes across Democratic and Republican governors are found in states where the manufacturing industry is relevant or the endowment of natural renewable resources is scarce. Interestingly, after extending the dataset until 2018, we find that governors party affiliation is no longer a significant determinant of renewable energy deployment, while there is persistence of lobbying pressures against renewables by the manufacturing sector. This is indeed in line with our predictions. In 2009 the Obama administration passed the American Recovery and Reinvestment Act which offers tax credits and payments to renewable energy developers through federal investments. This constitutes a clear structural break as federal programs overlap state-level policies and, afterwards, it becomes more difficult to disentangle the effects of state-level political factors. In addition, during the past decade, renewable energy sources have become more competitive in the energy market as the price of electricity from renewable power generation continued falling sharply. Given that renewable energy sources are less dependent on policy regimes subsidizing their deployment, market forces are increasingly confounding with political factors as the main drivers of renewable energy deployment.

Our findings contribute to the political economy literature on politicians' motivations and shed new light on the potential political pressures by opponents and supporters in the area of renewable energy policies. The results are in line with those found by List and Sturm (2006) and Fredriksson et al. (2011) and consistent with the assumption of politicians being primarily office motivated. Moreover, similarly to Pacca et al. (2021), our evidence suggests that politicians tend to deviate from their own policy preference in presence of strong interest groups. Further investigation could be developed by adding more complexity to the policy formation process, for example by considering also the role of state legislators and their interactions with lobby groups. In addition, building better and more precise measures of the lobbying activities that take place at the state level on environmental and climate policy constitutes an other important field for future research.

Our findings disclose important mechanisms and have policy implications. Industrial lobbies with a "higher" interest at stake might hinder the effectiveness of climate actions. This is particularly relevant for policies (as public support for renewable energy) that typically target expected long-term gains but impose short-run costs on the sources of polluting activities. A systematic analysis of the cost-effectiveness of renewable energy programs in terms of carbon abatement is out of the scope of this chapter. Nevertheless, our work contributes revealing the double challenge of the "green" transition, which requires not only to address the global externality of pollution but also to ensure the commitment of political actors, especially when climate policies are electorally costly.

1.A Data Appendix

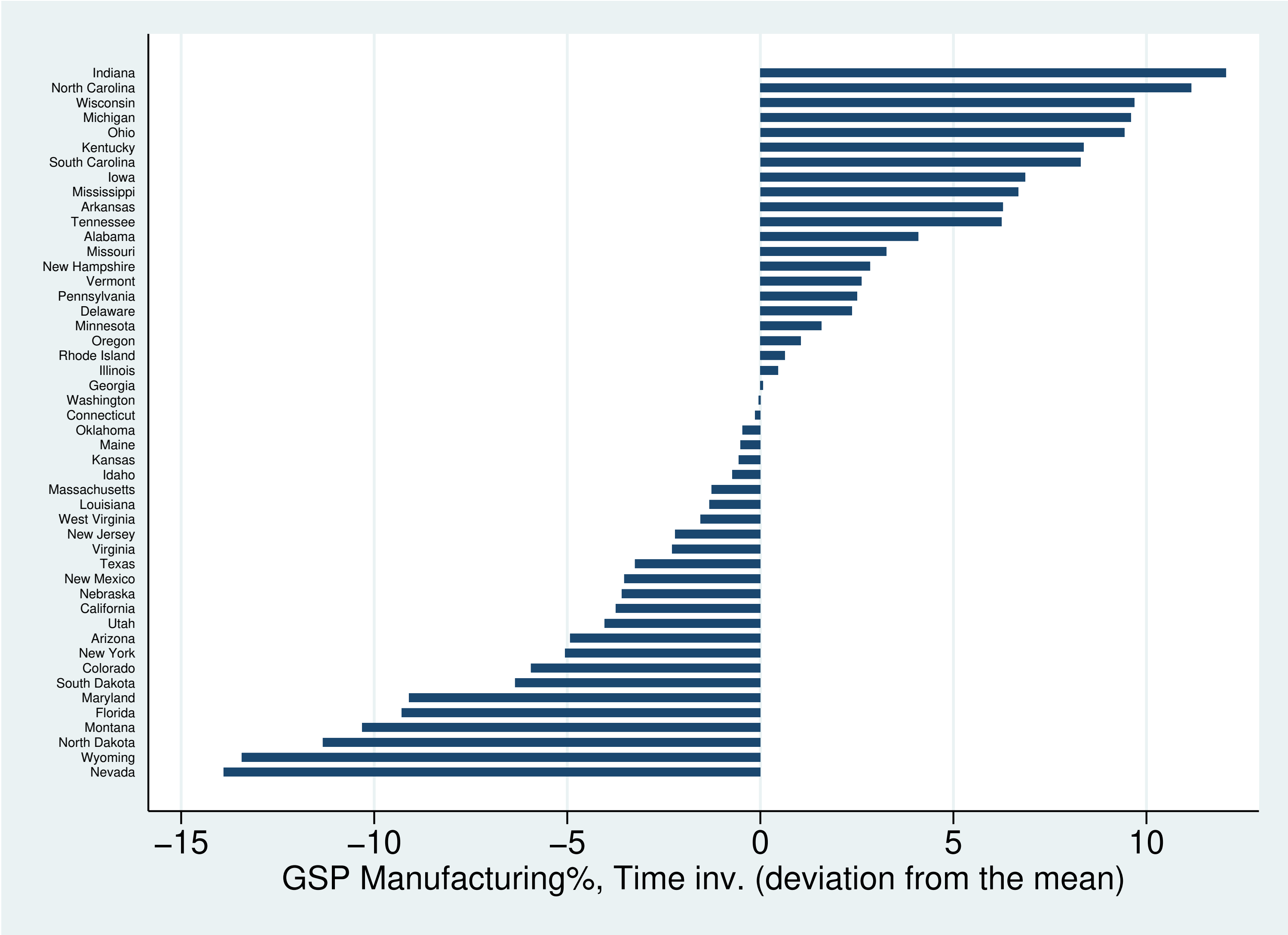
1.A.1 Renewable Energy Outcomes

The state level of renewable installed capacity is sourced from the U.S. Energy Information Administration (EIA) which provides detailed electricity information disaggregated by state-year. The variable is constructed as the sum of the nameplate capacity of all the wind, solar, geothermal and biomass power plant units belonging to the electric power industry (i.e., electric utilities, independent, commercial and industrial producers) in a given state. In line with the literature, we omit hydroelectric power capacity. In fact, it is not suitable to capture the stringency of recent renewable energy policies. Hydropower is a mature renewable technology whose electricity generation is already competitive in the market. Its installed capacity is not plausibly driven by recent public support schemes, but rather determined by pre-existing levels and hydrologic characteristics.

1.A.2 Manufacturing Sector Measures

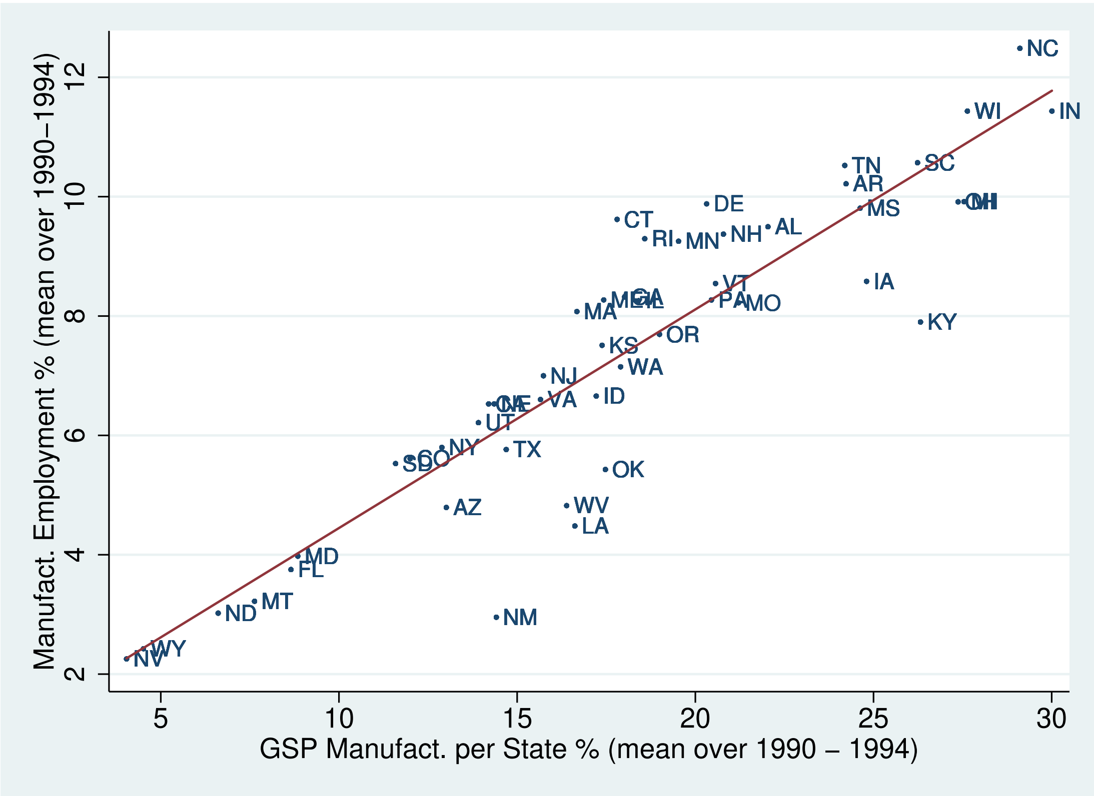
The data on the manufacturing sector are sourced from the Bureau of Economic Analysis (BEA), which provides aggregate measures for manufacturing industries of both GSP and employment for each state in each year. We mainly employ state time-invariant measures (calculated as the mean over the 4 years preceding our panel) to address the potential endogeneity between environmental policies and changes in economic activity across sectors. An alternatively time-variant measure calculated for each state in each year is used as an additional check. The variables are normalized to zero by detracting the sample mean. Figure 1.3 shows the variability of GSP manufacturing share (time - invariant) across states.

Fig. 1.3: GSP Manufacturing share per state (mean over 1990-1994)



Indiana and North Carolina are the states with the largest share from the manufacturing sector, while the manufacturing industry contributes the least to total GSP in Wyoming and Nevada. Figure 1.4 reports the scatterplots of the manufacturing employment share of the total population against the GSP manufacturing share, both time-invariant and calculated as the mean over 1990 - 1994. Despite the high correlation between the two measures, some states are relatively manufacturing-intensive despite their levels of manufacturing employment (e.g., New Mexico, Kentucky).

Fig. 1.4: GSP Manufacturing share and Employment Share



Notes: Time-invariant measures of GSP Manufacturing share and Manufacturing employment share are calculated as the mean over the period from 1990 to 1994. Data on total state employment, employment from the manufacturing sector, total Gross State Product (GSP) and GSP from the Manufacturing sector are sourced from the Bureau of Economic Analysis.

GSP manufacturing and employment of energy-intensive industries are constructed by borrowing from the sectors' classification by energy-use levels of Fredriksson et al. (2004) [32]. Energy-intensive industries correspond to "Primary Metal Manufacturing", "Nonmetallic Mineral Manufacturing" and "Paper, Paper Products, Printing and Publishing". The Bureau of Economic Analysis (BEA)

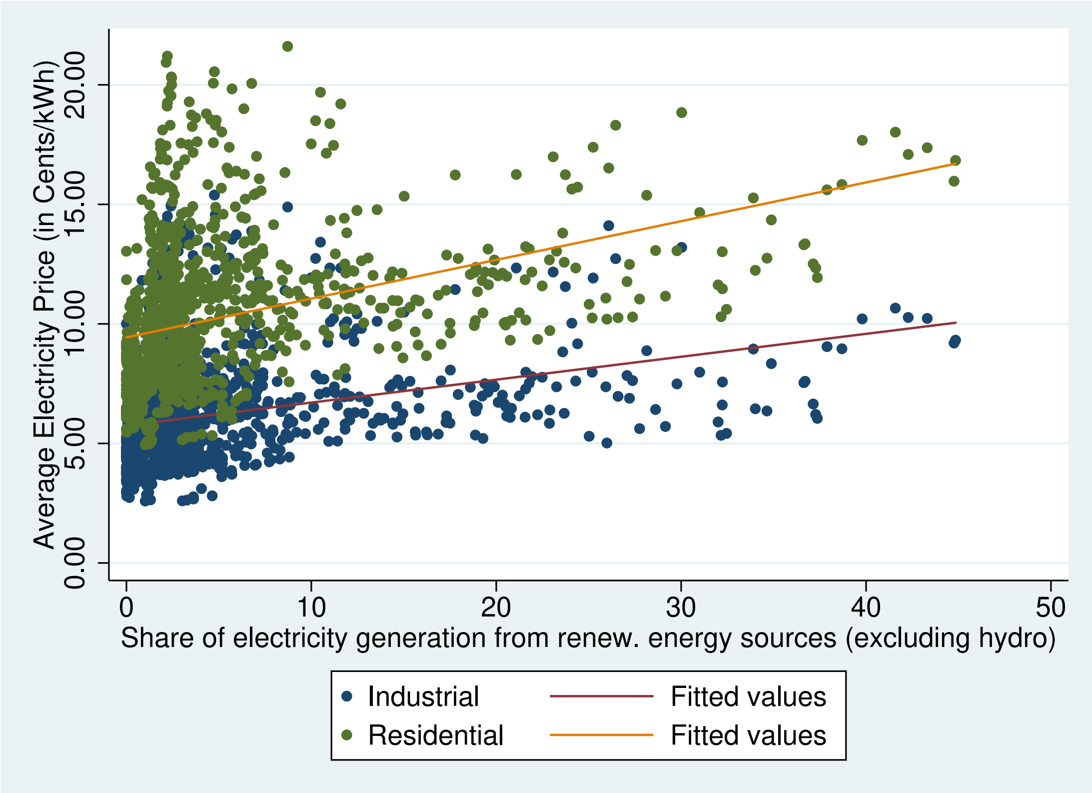
[32] Fredriksson et al. (2004) define energy intensity or energy efficiency as physical energy units per unit of value added. Their sectoral analysis consider OECD countries. We plausibly take that sectoral energy intensities are very similar for the U.S.

provides information about both the state value added by sectors and the relative employment levels. To construct a panel data comparable across year, we match the old SIC industry code with the NAICS industry classification (i.e., used after 1997) by recoding the sectors of interests. We then calculate the GSP share and the employment share of "Energy-intensive Manufacturing Industries". Again, we prefer to use time-invariant measures calculated over the 4 years preceding our panel for endogeneity issues.

In support to focusing on the manufacturing sector as a proxy of the lobbying activity against renewable energy policies, we first plot in Figure 1.5 a simple correlation graph between the average retail electricity prices to ultimate customers and the share of electricity generation from renewable energy sources (excluding hydropower) for each state-year observation over the period 1995 - 2018. The figure shows a positive correlation suggesting that an increase of the penetration rate of renewable energy sources is associated with higher electricity prices. Note that this increase seems to be more pronounced in the residential sector and that end-use electricity prices are far lower for industrial customers (due to large uses and higher voltages).

The second suggestive pattern is reported in Figure 1.6, which displays the correlation between the total average electricity prices (i.e., residential, commercial and industrial sector) per state and the relative GSP manufacturing share. Both variables are reported as means over the period the period 1995 - 2018. The graph seems to suggest that, historically, manufacturing-intensive states have been associated with lower electricity prices. However, we do not claim any causal inference from these simple correlations. In fact, it is not the purpose of this research to carry on a rigorous analysis of the effects of renewable energy on the electricity market or on its interconnections with economic sectors. These patterns rather inform about the potential political economy dynamics in action and bring additional support to the use of the manufacturing sector as an element of opposition to renewable energy.

Fig. 1.5: Electricity prices and electricity generation from renewable energy sources (1995-2018)



Notes: The figure shows the average electricity prices (for residential and industrial end-users) and the share of electricity generation from renewable energy sources (excluding hydropower) for each state-year observation for the period 1995 -2018. Data on state electricity prices and net electricity generation are sourced from the U.S. Energy Information Administration.

1.A.3 Natural Renewable Endowment Measures

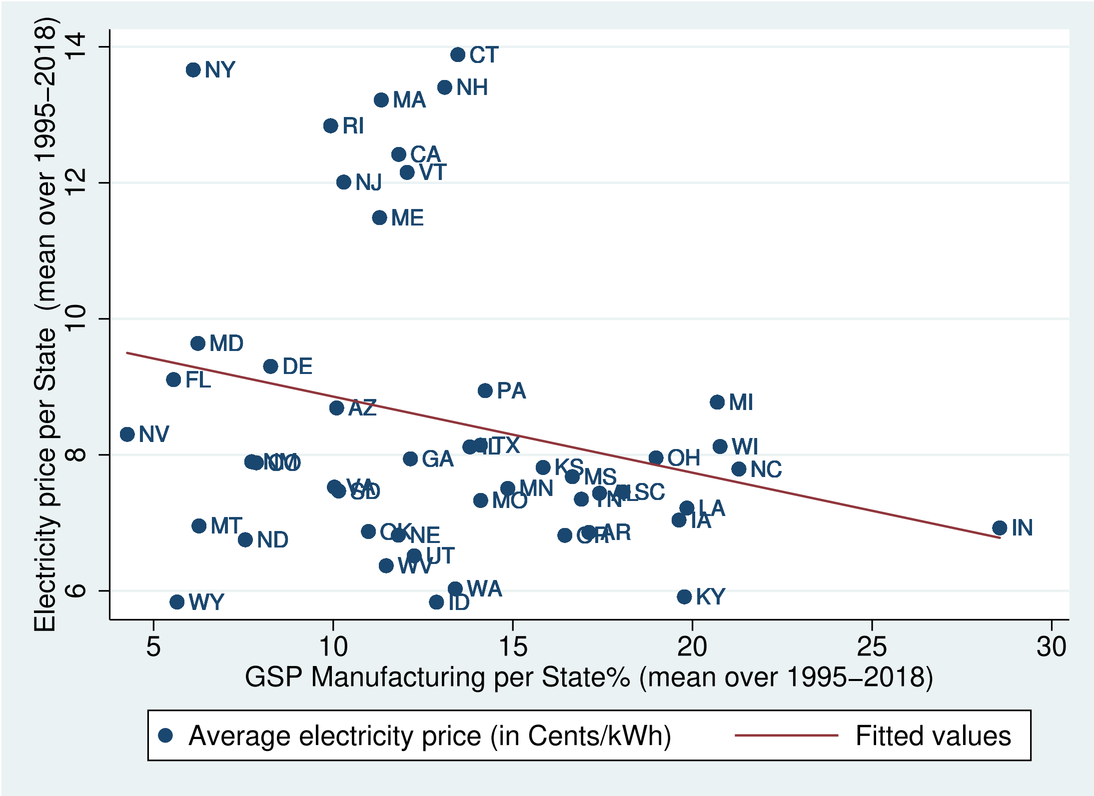
Wind potential is defined as the potential capacity (in MW) that could be installed from the development of the available land area [33]. The data is provided aggregated at the state level by the U.S. Department of Energy (WINDExchange online platform) based on the wind potential estimates of the National Renewable Energy Laboratory (NREL) [34]. Solar potential is measured as annual average daily total solar resource (in kWh/m2/day). It represents the potential of solar panels given daily solar radiation and land area [35]. The data is sourced by state

[33] The available land is calculated (in km2) as the total land area with a gross capacity factor for wind turbines of 35% and greater at 110 hub heights. Exclusion criteria for available land are applied including environmental criteria (e.g., national parks, conservation areas, national monuments) and land-use criteria (e.g., airfields, urban, wetland areas, non-ridge crest forests, areas with slope).

[34] NREL estimates for wind speed are averages over 2007 – 2013

[35] Solar resource is recorded over surface cells of 0.1 degrees in both latitude and longitude and using fixed flat plate systems tilted towards the equator (i.e., they reproduce the functioning of

Fig. 1.6: Electricity prices and GSP Manufacturing share per state



Notes: The figure plots the total average electricity price and the GSP manufacturing share in each state as the means over the period 1995 - 2018. Data on electricity prices are sourced from the U.S. Energy Information Administration. Data on GSP manufacturing industries are sourced from the Bureau of Economic Analysis.

from the solar radiation database of the National Renewable Energy Laboratory (NREL) [36].

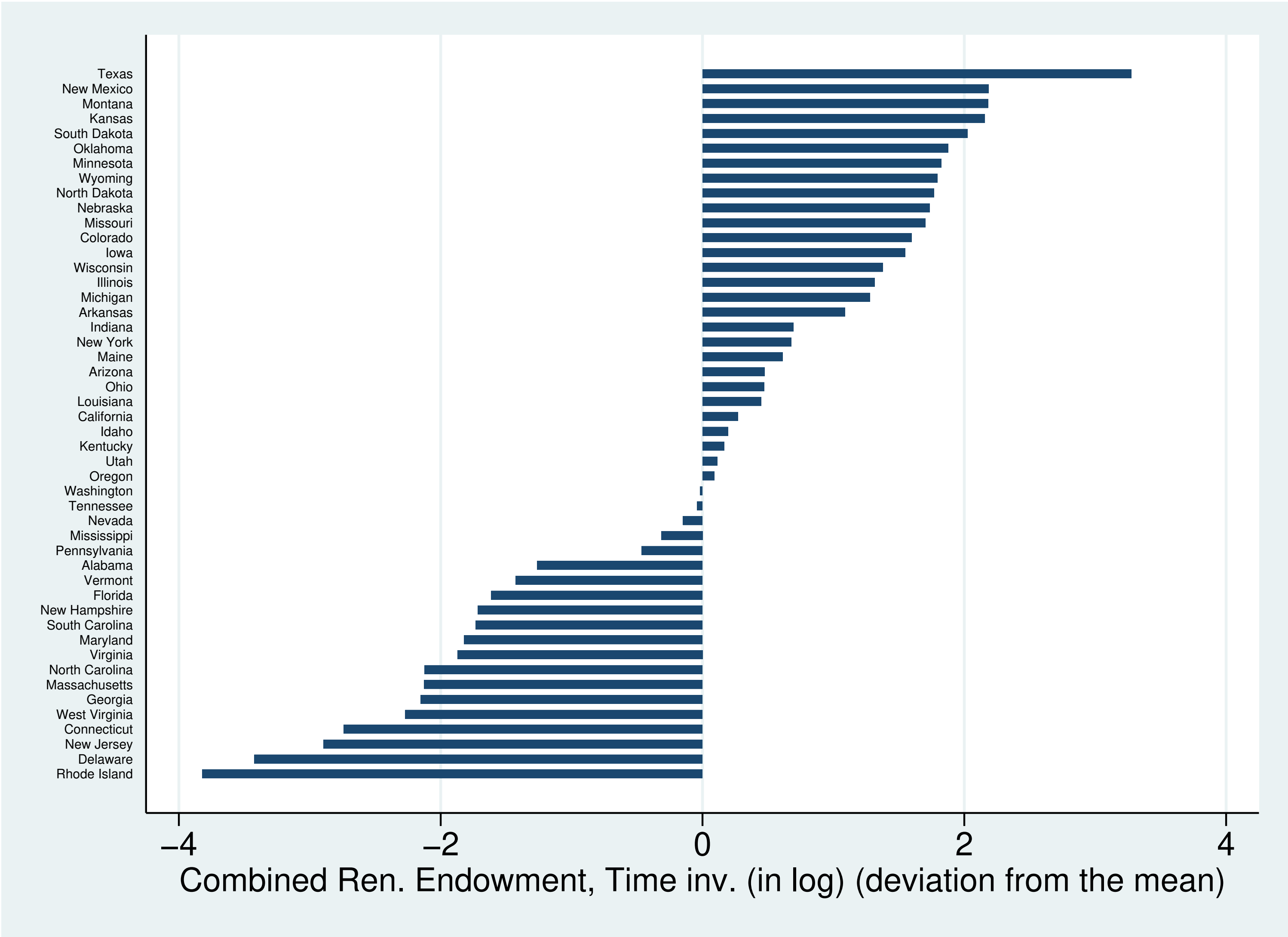
Wind and solar potential are sourced as time-invariant measures since both of them are defined as state annual averages calculated using data over multiple years. We assume them to be constant across time and independent from the year-span used as measurement benchmark. This assumption is not much of a concern given that these kinds of climatic variables do not significantly deviate from their annual means over decades. These variables are expressed in logs and as deviations from the sample mean. Figure 1.7 shows the cross-state variation of the combined indicator of solar and wind potential. Higher scores equal higher levels of natural renewable endowment which, in turn, is assumed to attract the interests of clean energy producers. Prominent examples of abundance in natural renewable resources are states characterized by windy lands (i.e., mainly due

solar panels).

[36] NREL estimates for solar radiation are averages over 1998 - 2009

to the presence of mountains and hills) and located in Southern sunny areas (e.g.,Texas and New Mexico). North-East states (e.g., Rhode Islands, Delaware and New Jersey) display, instead, the lowest levels of renewable energy potential.

Fig. 1.7: Natural Renewable Endowment (combined wind and solar) per state



CHAPTER 2

Foreign import competition and green innovation: the impact of Chinese trade exposure on technical change in Europe

Abstract

This chapter examines the impact of Chinese import competition on innovation. By using detailed patent information on the manufacturing industries of thirteen European countries and trade data from 1995 to 2015, I estimate and compare the effect of rising Chinese imports on the growth rates of industry-wide patent stocks in generic and green inventions. The results reveal that Chinese import competition had no overall impact on total innovation at the industry level. However, the trade shock accelerated technical change directed towards green innovations, especially in lagging industries. I argue that an escape-competition effect of European firms to crowd out and differentiate from new Chinese competitors could motivate the empirical evidence. My findings account for the endogeneity of trade exposure and are robust to confounding sectoral patenting trends.

2.1 Introduction

The most relevant episode of trade liberalization of the past two decades has been the China's accession to the World Trade Organization. This event has been followed by the spectacular rise of China as a major world exporter. In light of the rapid surge of Chinese trade, its impact on the economies of the developed world has gained relevance. The political and economic debate has evolved around the implications of such a shock on the manufacturing sector of Northern countries, for example regarding the consequences in terms of productivity, employment and technological advancement. From the perspective of domestic firms, trade liberalization could either bring more import competition or provide export opportunities. This chapter focuses on the effect of rising import competition from China on technical change in Europe.

Economic theory has devoted a great interest on how product market competition stimulates innovative activity, but the findings on the relationship between competition and innovation are still ambiguous. The Shumpeterian theory posits that the exposure to increased market competition lowers firms' expected profits, thus reducing their incentives to innovate. Aghion et al. (2005) reconcile the endogenous growth theory with the causal evidence on the positive correlation between innovation and competition by arguing that increased competitive pressures by potential new entrants stimulate innovation by incumbent firms to "escape competition". The theoretical framework predicts the effect to prevail whenever firms compete at similar technology levels, while the Shumpeterian discouragement effect dominates for laggard firms as they have lower chances to beat the competition of new entrants.

The empirical evidence on the effect of import competition on innovation is still puzzled as well. Bloom et al. (2016) find that Chinese import competition led to increased technical change within European firms. Not only do they find evidence on a within-firm increase in the volume of innovation but they also support that the China trade boom induced a reallocation of jobs toward high tech firms and that it reduced the survival probabilities of low-tech firms. Conversely, in a study on US firms, Autor et al. (2020) find an overall adverse effect of the intensified competitive pressure from China causing to stifle domestic innovation. The literature has mostly unveiled the pro-competitive effects of trade liberalization, market size and improved access to foreign markets on productivity [Melitz (2003), Melitz and Ottaviano (2008) and Lileeva and Trefler (2010)] and on technology upgrading and innovation [Bustos (2011) and Coelli et al. (2022)]. However, when focusing on foreign import competition, the findings are still inconclusive.

This chapter attempts to bring new empirical evidence to the debate on the impact of a low-wage country shock on Northern technical change. I first study the impact of rising Chinese import on innovation in European countries at the industry level. I use patent data from the PATSTAT database to construct measures of innovation activities. Import competition is measured as trade exposure to Chinese imports at the industry level. The panel consists of 40 industries across 13 European countries and the exposure period considered spans from 1995 to

2015. Rather than studying firm-level innovation, my approach focuses on the within-industry technical change which captures both the within-firm innovation response to Chinese imports and the within-industry reallocation of innovative activities from low-tech to high-tech firms.

The availability of new rich patent data sources as provided by PATSTAT allows us to go further the work by Bloom et al. (2016). In particular, the detailed information regarding technology fields and new classification systems enables investigating the direction of technical change, i.e. whether the impact of the China trade shock was stronger or weaker on a particular class of inventions and technologies. I focus on green innovations and classify them by looking at subgroups of the "Y02 classification" which was recently developed by the European Patent Office to map technologies for mitigation and adaptation against climate change. I argue that the technological upgrading towards green inventions by European firms could be motivated to maintain the comparative advantage over Chinese firms. The argument can be viewed through the lens of the escape-competition framework: European firms were stimulated to innovate more and specialized in green technologies as a way to escape from the increased competitive pressure from Chinese firms. Indeed, European firms had (at least when trade barriers fall between EU and China) a large technological lead over China. Intuitively, imports from a low wage country made less profitable for European firms to keep producing low-tech good. Evidence on the interplay between high-tech industry capacity and green production has been recently provided by Bontadini and Vona (2020). In this context, green specialization entails both technological upgrading and differentiation from low-tech competitors.

A major empirical challenge in identifying the effect of the trade shock on innovation is the endogeneity of trade exposure to Chinese imports. Following Autor et al. (2014), the identification strategy relies on isolating the supply-driven component of rising Chinese imports by instrumenting the changes in industry-specific EU-countries imports with contemporaneous changes in import exposure in other OECD countries. This approach allows to address both the correlation between changes in Chinese imports and unobserved demand-side domestic shocks and the simultaneity between technology upgrading and trade exposure as well. In order to control for patenting trends that might be mistakenly attributed to the China trade shock, I also include in the empirical specifications industry long-run (pre-) trends in patent activity and perform several robustness checks.

The results show that increased import competition from China did not lead to an increase in total innovation activity at the industry level. However, trade exposure to Chinese imports accelerated technical change towards green inventions. These findings seem to suggest that European firms directed innovation towards high-tech and "green" rather than generic products to beat their new competitors. The overall effect masks considerable heterogeneity across industries as the rate of green technical change was faster in industries far from the technological frontier. Given that the analysis is carried out at the industry level, the results seem to point to a possible within-sector reallocation effect. In other words, the faster technical change of lagging industries might be motivated by the exit from the market of low-tech firms due to the increased Chinese import competition and to the within-sector reallocation of innovation activity from low-tech to high-tech firms. My findings add new evidence to the literature on import competition and innovation, while exploring a new field of research on trade and green specialization where the empirical evidence is still rather scarce.

The rest of the chapter is organized as follows. In section 2.2, I present the theoretical background and the hypothesis of this work. Section 2.3 outlines the empirical strategy and discuss the identification issues. In section 2.4, I present the data and some descriptive evidence. Section 2.5 shows and discuss the results, while section 2.6 provides the robustness checks. Finally, a brief conclusion and discussion are presented in section 2.7.

2.2 Theoretical Background and Hypotheses

How product market competition affects firms' incentives to innovate is a long-standing interest in both the theoretical and empirical literature. The Shumpeterian growth theory has generally argued that a more competitive marketplace reduces firms profit margins resulting in lower incentives for firms to innovate. According to the Shumpeterian paradigm, the prospects of capturing monopoly rents are the crucial rewards for innovators. The idea that R&D efforts are motivated by monopoly rents is featured in several endogenous growth models where innovative activity is carried out by incumbent firms to maintain their market power or by new entrants to take over the position of the monopolist through new and better products [see Aghion and Howitt (1992)].

More recently, the "step-by-step" model of innovation by Aghion et al. (2001) reconciles the Shumpeterian paradigm with the empirical evidence that, contrarily to economic theory, points to a positive relationship between competition and innovation. The underlying assumption is that, in each industry, firms must catch up with the technological leader before leading over the rival. First, this framework relaxes the assumption of monopolistic competition. Second, it predicts that, under some circumstances, increased product market competition may encourage firms to innovate more. When the competition is “neck-and-neck” (i.e., when firms compete at similar technological levels), firms increase their innovative activity in order to escape from a situation of higher competition that reduces their profits. This effect is called *escape-competition* effect. Conversely, in industries that are not neck-and-neck, the effect of increased competition on innovation is ambiguous. Laggard firms’ incentive to innovate will be discouraged whenever new market entries stifle their hopes to become a leader. In this case, a *discouragement* effect may dominate the *escape-competition* effect. Accordingly, Aghion et al. (2005) find that the relationship between competition and innovation is not linear but it follows an inverted-U shape pattern. Whether the escape-competition effect prevails on the discouragement effect ultimately depends on the initial degree of competition [1].

Other two important insights are derived from the work of Aghion et al. (2005) and Aghion et al. (2009). First, within a given sector, the technology gap between leaders and followers increases with more competition [2]. Second, this holds true also between sectors: the escape-competition effect is stronger in sectors where the competition between firms is neck-and-neck rather than in sectors with a large spread in firms’ technology levels [3]. Thus, increased market competition widens the technological gap not only *within* but also *between* sectors. This intuition captures the essence of the distance to the frontier framework: firms’ innovation response to more competition depends on their location on the technological frontier.

One key feature of the distance to the frontier framework developed by Aghion et al. (2005) is that neck-and-neck competition is engaged between firms with similar technology levels. The model typically assumes and considers the entry threat of technology advanced outsiders [4]. By focusing on this kind of threat, the

[1] When product market competition is initially low, there are no incentives for leaders to innovate and, thus, most sectors involve in neck-and-neck competition. An increase in competition results in a faster innovation rate as the escape-competition effect dominates. On the other hand, when initial competition is high, there are little incentives for the laggards to innovate. An additional increase in competition results in a slower innovation rate.

[2] Following the dynamic model structure, as firms try to escape competition, the spread in technology increases within the industry.

[3] Aghion et al. (2005) find that, for any given level of competition, the inverted U-shape relationship is steeper in neck-and-neck sectors.

[4] The empirical testing ground of Aghion et al. (2009) consider technologically advanced entry by greenfield entry of foreign entries and they instrument it by policy reforms in the EU single market program and U.K privatization.

prediction is such that more competition fosters innovation in firms and sectors that are close to the technological frontier, while it reduces innovation's incentives in firms and industries that lag behind.

However, I argue that this implicit model assumption does not fit the case of increased trade exposure to Chinese imports. The competitive pressure followed the trade liberalization with China was mainly driven by lower costs and comparative advantages in the labor market rather than (at least initially) being motivated by the prospects of Chinese firms to race for technological leadership. As a matter of fact, at the time of China accession to the WTO, most of European firms had a large technological hedge over Chinese firms. It is therefore more plausibly to conceive that low-tech foreign outsiders engaged a neck-and-neck competition with firms that were mostly located far from the technological frontier rather than with technologically advanced firms. Thus, I expect that the firms' innovation response differs in the context of exposure to China trade.

Several studies closely relate and support this intuition by focusing on the implications of trade exposure to low-wage countries. On the U.S. manufacturing, Bernard et al. (2006) shows that industry exposure to low-wage country imports induced a within-industry reallocation towards capital-intensive plants. Moreover, they provide evidence that firms switched industries and adjusted their product mix consistently with comparative advantage theory. Bloom et al. (2016) find that high-tech European firms have been relatively sheltered from Chinese imports while low-tech firms have been adversely hit by Chinese competition in terms of employment and survival probabilities. More generally, these results relates also to the firm heterogeneity literature on the pro-competitive effect of trade liberalization [see Melitz (2003) and Melitz and Ottaviano (2008)].

In what follows, I borrow from the logic of the distance to the frontier model. However, I argue that China import competition is a low wage country shock. Imports from a low wage country make less profitable for European firms to produce low-tech goods and increase incentives to move up to upgraded products, thus stimulating faster technical change. In the context of China trade exposure, I expect that the escape-competition effect prevails in firms and sectors far from the frontier rather than in frontier innovators. Laggard firms are those operating in industries with a low technological level. These firms are therefore expected to intensify their innovation activity to survive and beat their low-tech new competitors. On the other hand, technological advanced firms benefit from a technological lead over low wage imports. They do not have any incentive to innovate more as the market entry of low-tech outsiders does not constitute a threat for their market power. This result in a modification in the predictions of the distance to the frontier framework. I expect that increased competition from low-tech firms may trigger the catch up of industries that are initially far from the technological frontier.

Building on this theoretical background, three testable hypotheses are formulated:

Hypothesis 1 *An increase in import competition enhances faster technical change and innovation for firms operating in exposed industries (classic escape-competition effect).*

Hypothesis one reflects the classic escape-competition effect: European firms escape Chinese import competition by innovating more and by developing new technologies. Because China trade exposure is observed by country-industry, I study whether increased import exposure induced an increase in total patenting activity by firms aggregated at the country-industry level.

Hypothesis 2 *Exposure to low-wage country imports induces firms to direct innovation towards high-tech and "green" products rather than generic products to beat their new competitors (directed escape-competition effect).*

Hypothesis two closely relates to the previous escape-competition argument but it allows to better identify the direction of technical change. In particular, instead of adopting generic new products, I expect European firms to intensify their innovation activity towards technologies that can effectively ensure them a technological lead over Chinese imported products. I test this hypothesis by comparing the growth rates of patenting activity in environment-related "green" products with the growth rate in total patenting activity. I choose to focus on "green" innovation for several reasons. First, European firms show a relevant initial lead over Chinese firms in terms of "green" innovation which I define as technologies with potential for climate change mitigation. This is not only supported by the literature but by looking at the comparison between the European and China averages of the green knowledge stock (as a fraction of total knowledge stock) by NACE industry over the period 1978-2000 (Figure 2.7). Second, there is growing evidence showing that "green" production concentrated in high-tech industries [Bontadini and Vona (2020)]. The impact of foreign competition is therefore likely to be different of non-green and green innovation. Third, I argue that directing towards "green" inventions may also be part of market strategy for European firms to differentiate from cheaper Chinese products. Thus, I investigate whether green innovation grew faster than total generic innovation. The difference in the two rates may be motivated by the adjustment of European firms and may disclose potential shifts in their product mix towards high-tech and "green" products that are less exposed to Chinese import competition.

The third hypothesis regards the impact of Chinese exports based on the different levels of distance from the technology frontier:

Hypothesis 3 *The directed escape-competition effect is stronger in industries where firms initially compete neck-and-neck with low-tech Chinese competitors, i.e. in country-industries far from the green technological frontier and where the distance is measured at the industry level ("reverse" distance to the frontier and compositional effect).*

Hypothesis three is my "reverse" distance to the frontier argument. Intuitively, firms and industries that are initially close to the technological frontier are not threatened by the market entry of competitors with a lower level of technology. Thus, they do not show any incentive to innovate more or to switch their product mix. Therefore, I do not expect the China trade boom to foster innovation in a country-industry that is already initially populated with large fraction of high-tech and "green" firms. On the other hand, firms and industries that compete at similar technology levels with Chinese firms have a strong incentive to redirect their innovation activity towards new products and technologies that can beat their competitors. The distance is therefore measured by comparing country-industries with the respective country-industry located at the green technological frontier. At the industry level, the main driver of the industry technological upgrading could be a *within* sector compositional effect: within a given lagging industry, the (smaller) fraction of more productive and technological advanced firms grows more while other laggards do not survive to the Chinese competition shock. Thus, I expect that the difference between the growth rate in "green" inventions and generic products is larger in country-industries that are located far from the technological frontier. In other words, a catch up mechanism of industries populated by firms that are on average far from the frontier may be driven by the escape-competition effect.

2.3 The Empirical Strategy

2.3.1 Empirical Modelling

Based on the theoretical background presented above, in this section I present the empirical specification and discuss the identification strategy. The central empirical goal is to estimate the impact of rising Chinese import competition on technical change at the country-industry level.

To start with testing hypothesis one and two, I compare the coefficients obtained in the following baseline equations where j denotes industries, n denotes countries and t denotes years:

$$\Delta K^{g}_{jnt} = \alpha_{nt} + \beta_1 \Delta IMP^{CN}_{jnt} + \gamma X_{jn} + \epsilon_{jnt} \tag{2.1}$$

$$\Delta K^{t}_{jnt} = \alpha_{nt} + \beta_2 \Delta IMP^{CN}_{jnt} + \gamma X_{jn} + \epsilon_{jnt} \tag{2.2}$$

$$\Delta K^{g}_{jnt} - \Delta K^{t}_{jnt} = \alpha_{nt} + \beta_3 \Delta IMP^{CN}_{jnt} + \gamma X_{jn} + \epsilon_{jnt} \tag{2.3}$$

The dependent variable, ΔK^{g}_{jn} (ΔK^{t}_{jn}), represents the change in green (total) knowledge stock in industry j and country n between period t and $t-5$. I define the dependent variable as $\Delta K_{jnt} = (K_{jn,t} - K_{jn,t-\tau})/(0.5K_{jn,t} + 0.5K_{jn,t-\tau})$ which is a standard approximation of a log change over a time span τ [5]. The growth in the Chinese import share ΔIMP^{CN}_{jn} is the proxy for rising import competition from a low-wage country. The variable is defined as the change in the share of the imports originating from China (M^{CN}) of total world import value (M^{World}) in industry j and country n over the period τ: $\Delta IMP^{CN}_{jn} = (M^{CN}/M^{World})_{jn,t} - (M^{CN}/M^{World})_{jn,t-\tau}$.

Using long 5-year differences (i.e., $\tau = 5$) to study innovation growth has a double advantage over specifications in levels. First, it allows to difference away country-industry fixed effects that do not vary over time. Second, long differences capture the long time response of innovation to the growth in the exposure to Chinese imports. I use overlapping 5-year differences (e.g. $t_1 = 2000 - 1995, t_2 = 2001 - 1996$) to maximize the sample size. I include a full set of country dummies interacted with time dummies, α_{nt}, in order to absorb country-specific macro shocks; X_{jn} is a vector country-industry specific controls (i.e.,

[5] I follow Autor et al. (2020) and use the proportion change scaling of K rather than the log change so that it is also defined for units whose patent stock was zero at the beginning of a period. The two specifications are either way highly correlated. I show as a robustness check that using the log change do not change the results even if the sample size becomes smaller due to some zero values in the dependent variable at the beginning of a period.

pre-period knowledge stocks) and ϵ_{jnt} is the error term. I cluster standard errors at the country-industry pair level in order to correct for the serial correlation in the errors generated by the time-series structure.

The empirical strategy relies on comparing the growth of green patent stock (or knowledge stock) with the growth of total patent stock. Hypothesis one predicts that $\beta_1 > 0$ and $\beta_2 > 0$, i.e. that rising import competition may induce faster technological change in either green and generic products. In equation (2.3), I explicitly test hypothesis two regarding the direction of technical change. If green knowledge stock grew faster than total knowledge stock due to the China trade shock, I expect β_3 to be significant and positive. Note that specification (2.3), differently from equation (2.1), allows us to more precisely estimate the impact of China import competition. In fact, by subtracting ΔK^t in the left hand side of the equation, I purify from the correlation between total and green innovation. In this way, β_3 fully captures the impact of import competition on green rather than total innovation. It also helps controlling for wider innovation trends at the industry level that can be confounded with trade shocks.

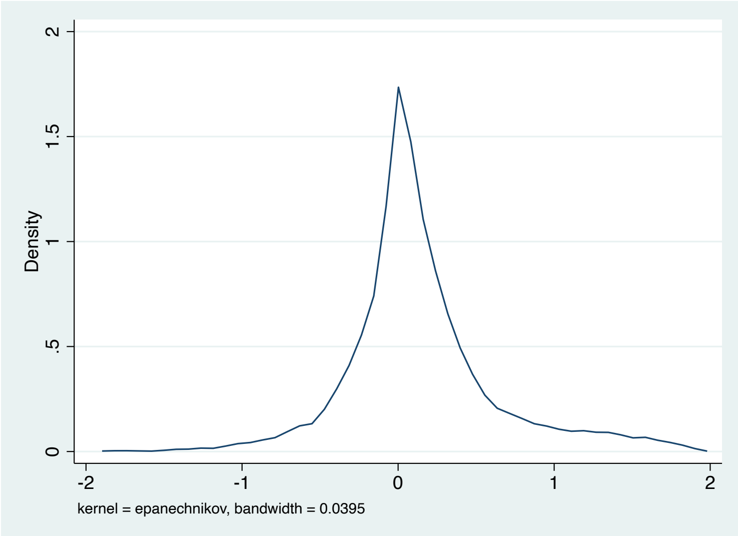
The outcome variable of innovation activity is the change in the knowledge stock. The knowledge stock is defined as the cumulative count of patents in an industry j and country n until year t:

$$K_{jnt} = \sum_{s=1978}^{t} p_{jnt} \tag{2.4}$$

where p_{jns} is the number of unique granted patents by all firms in country n in year s and associated to industry j. I only count corporate patents to focus on the innovation response to import competition by firms. The proportional change ΔK_{jnt} as defined above gives the average growth rate of the knowledge stock and it provides a measure of the flow of new inventions occurred during a 5-year period. I follow Coelli et al. (2022) by focusing on the change in the stock over a long period rather than on the simple patent count p_{jnt} in order to smooth out the highly skewed distribution of patent counts. As shown in Figure 2.1, the main dependent variable used ($\Delta K^g_{jnt} - \Delta K^t_{jnt}$) is not subject to the usual problems of zero inflation and skewedness that typically occur when using highly disaggregated patent counts as dependent variable [6].

[6] I find similar results when I use the same empirical specifications and simple patent counts aggregated at lower level as dependent variable. This seems to be motivated by the fact that grouping patent counts to a less disaggregated level (NACE 2-digit) reduces the number of zeros and the skewness of patent data and lead to comparable results with specifications considering changes in the stock as dependent variable.

FIG. 2.1: Kernel density estimate of the main dependent variable $\Delta K^{g}_{jnt} - \Delta K^{t}_{jnt}$



Notes: The dependent variable refers to equation 2.3.

2.3.2 Identification

Even if differencing eliminates time-invariant unobserved heterogeneity and country-year dummies absorb time effects, the baseline specifications still suffer from other potential econometric concerns. When estimating the equations above, the first identification issue that I tackle is the potential endogeneity of trade exposure to Chinese imports. Endogeneity may arise because ϵ_{jnt} contains an important time-varying omitted variable that is correlated with ϵ_{jnt}. Indeed, changes in Chinese imports are likely to be correlated with unobserved domestic shocks to European industries (e.g., demand-side shocks) that determine both import demand and innovation activity. There may also be simultaneity between technology shocks and Chinese imports: a positive technology shock can make it harder for low-tech Chinese firms to export their products in the European countries.

Given these potential sources of endogeneity, the coefficients β_1, β_2 and β_3 are subject to potential upward or downward biases and inconsistency without an appropriate identification strategy. I use a similar approach as the one proposed by Autor et al. (2014) and I instrument ΔIMP^{CN}_{jnt} with the following instrumental variable:

$$\Delta IMP^{CN}_{jnt} = \Delta IMP^{CN}_{jt,other} \tag{2.5}$$

where $\Delta IMP^{CN}_{jt,other}$ is the change in the Chinese import share in industry j between period t and $t-5$ for a group of five OECD rich countries that does not include any European countries [7]. Thus, the first stage regression of the model is:

$$\Delta IMP_{jnt}^{CN} = \alpha_{nt}^{IV} + \psi \Delta IMP_{jt,other}^{CN} + \phi X_{jn} + \epsilon_{jnt}^{IV} \tag{2.6}$$

The validity of this approach in studying the China trade shock has been extensively discussed in Autor et al. (2013) and Autor et al. (2014). The intuition for the instrument is that the China trade shock similarly hits high-income economies and it is equally driven by supply-side determinants such as lower production costs, competitive advantages, falling tariffs and trade barriers in China manufacturing exporting sectors [8]. The instrumental variable strategy aims at isolating the effect on innovation of the supply-driven component of rising Chinese imports, identified by the covariance between the industry-level Chinese import share in European countries and the import share in other OECD countries. Another desirable benefit of the instrument is that it mitigates any attenuation bias due to measurement errors which are particularly exacerbated in differenced specifications with fixed effects [see Wooldridge (2001)].

Another major econometric concern is that there may be confounding trends and pre-trends in patenting activity that are correlated with the supply-driven component of Chinese imports. The problem clearly arises due to the lack of satisfactory counterfactual when studying the China trade shock. One may rightfully question whether innovation could have spurred or not even in the absence of rising competition pressure of Chinese firms. Since this problem cannot be naturally addressed by the instrumental variable strategy, accounting for industry trends is crucial for the identification and for the interpretation of the results as causal. The importance of this issue is even more pronounced in the case of green innovation as industry-level growth trends that are driven by environmental regulation tightening over time may be mistakenly attributed to the China trade shock.

To absorb growth trends in patenting, I apply a full set of industry or country-industry fixed effects to the differenced equations. For example, equation (2.3)

[7] The group of countries includes the United States, Canada, Australia, Japan and New Zealand. I obtain similar results by considering subgroups or excluding some of these countries, for example the US. HS trade data are sourced from the CEPII-BACI dataset and aggregated at the industry level with the same procedure used for the European countries.

[8] The identifying assumption is that industry import demand shocks are not correlated across high-income countries (see Autor et al. (2014)). Since this could be problematic when considering the US and the European countries, I try excluding the US from the group of high-income countries as a robustness check and I note that the results do not change.

becomes:

$$\Delta K^g_{jnt} - \Delta K^t_{jnt} = \alpha_{nt} + \theta_{jn} + \beta_4 \Delta IMP^{CN}_{jnt} + \epsilon_{jnt} \tag{2.7}$$

where θ_{jn} are country-industry dummies or industry-wide dummies (i.e. θ_j). I argue that equation (2.7) is the preferred empirical specification as I am disentangling green from total innovation, I am eliminating country-specific industry trends as well as addressing endogeneity in Chinese imports by instrumenting for rising imports in third countries [9]. As a robustness check, I also perform a falsification test that regresses the change in industry-level knowledge stock during the period before the China trade shock (1978-1990) on the future change in industry-level Chinese import share (1995-2007).

2.3.3 Heterogeneity and Distance to the Frontier

After addressing the challenges to the identification strategy, I investigate potential heterogeneity and non-linearity in the effect of increased Chinese import competition on innovation. I have argued in hypothesis three that, in the context of the China trade shock, more import competition may induce a distance to the frontier effect but "reverse" with respect to the case considered by Aghion et al. (2005). The intuition is such that the escape-competition effect is stronger in those industries where the level of green innovation is lower, i.e. where the average firm is more exposed to the neck-and-neck competition with low-tech Chinese firms. On the other hand in industries close to technological frontier, I expect that the import competition will have a lower effect on industry-level growth rate in green innovation, as a smaller fraction of firms will be threatened by low-tech foreign competitors.

An initial strategy to inspect potential heterogeneity in the effect regards conditioning the effect of Chinese import competition on the lagged industry technology level. By extending the preferred empirical specification (2.7), I obtain:

$$\begin{aligned}\Delta K^g_{jnt} - \Delta K^t_{jnt} = \alpha_{nt} + \theta_{jn} + \beta_1 \Delta IMP^{CN}_{jnt} + \beta_2 lnK^g_{jn,t-5} \\ + \beta_3(\Delta IMP^{CN}_{jnt} \times lnK^g_{jn,t-5}) + \epsilon_{jnt}\end{aligned} \tag{2.8}$$

where $lnK^g_{jn,t-5}$ is the (log) level of green technology stock in industry j, country

[9] Another way of eliminating the effect of country-specific industry trends is by double differencing. I try this option as a robustness check and I note that my results remain unchanged.

n and for the period $t-5$ to reduce any endogeneity problem. I am particularly interested in whether the growth in Chinese import share has a disproportionate effect on the growth of green innovation in country-industries where the (lagged) level of green technology stock is lower. If the escape-competition prevails in industries where the average (past) green technology stock across firms is low (i.e. where firms closely compete with Chinese imports), then I would expect $\beta_3 < 0$.

To precisely empirically assess the predictions of the distance to the frontier argument, I need an industry-level measure of distance that captures how far an average firm in a given country-industry is located with respect to the green technological frontier. The chosen method is to consider the ratio of green over total knowledge stock at the country-industry level (i.e., $K^{g/t}_{jnt} = K^{g}_{jnt}/K^{t}_{jnt}$) and to measure the distance as the ratio between the level of a nonfrontier country-industry pair and the in-sample frontier industry with the highest green knowledge ratio per year. Formally,

$$D_{jnt} = \frac{K^{g/t}_{jnt}}{max(K^{g/t}_{jnt})} \tag{2.9}$$

where $max(K^{g/t}_{jnt})$ is the maximum value of the green knowledge ratio within an industry-year and the ratio D_{jnt} measures the distance of a nonfrontier industry j in country n at year t to the frontier industry. Therefore, values of D_{jnt} close to one indicate industries close to the frontier, while the value decreases up to zero for industries that are far from the green technology frontier. In order to study whether the effect of increased Chinese competition on the innovation output varies with the industry-level distance to the frontier, I proceed by adding to the preferred specification a distance interaction term as follows:

$$\begin{aligned} \Delta K^{g}_{jnt} - \Delta K^{t}_{jnt} = \alpha_{nt} + \theta_{jn} + \beta_1 \Delta IMP^{CN}_{jnt} + \beta_2 D_{jn,t-5} \\ + \beta_3(\Delta IMP^{CN}_{jnt} \times D_{jn,t-5}) + \epsilon_{jnt} \end{aligned} \tag{2.10}$$

where $D_{jn,t-5}$ is the distance indicator of industry j in country n at time $t-5$ and it is lagged in order to avoid endogeneity. If escape-competition dominates when firms compete at a similar technological level, the prediction is such that more intense competition from low-tech Chinese firms will spur green innovation in industries where the average firm is located far from the green technology frontier, i.e. $\beta_3 < 0$.

2.4 Data

2.4.1 Patents

To measure innovation and construct the dependent variable based on changes in the knowledge stock, I use patent data sourced from the European Patent Office's (EPO) worldwide statistical database (henceforth PATSTAT) [10]. This database contains the bibliographical information of patents from most patent offices in the world. The advantages and drawbacks of using patent data to measure innovation have been extensively discussed by the literature [see Griliches (1990)]. Among the methods used in the literature, patent data proxy for the innovation output, while R&D expenditures proxy for the input used in the innovation process. These two measures are known to be strongly correlated indeed [Griliches (1990)].

Patent documents are particularly appealing because they are categorized using the International Patent Classification (IPC) system [11]. Therefore, patents can be disaggregated into specific technological fields that are comparable at the international level. For the purpose of the analysis, this key feature has a double advantage. First, PATSTAT contains a mapping scheme that matches the technology classes (IPC codes) of each patent application to the industrial sectors (NACE revision 2) that are linked with the technology [12]. The mapping scheme allows us to allocate technology classes to NACE 2-digit industries or, if a more disaggregated level is available, to NACE 3-digit sectors [13]. Since I group patent applications by using this built-in assignment scheme, I obtain a measure of innovation activity at the industry level that is reliable and comparable across different countries. Moreover, this method directly exploits the information contained in patent documents. I do not need to infer industrial affiliation from other data sources such as firm-level datasets and I do not have to restrict to a fixed set of industry codes assigned to each firm [14] .

[10] I use the Autumn 2020 PATSTAT version.

[11] The International Patent Classification (IPC) was developed by the World Intellectual Property Organisation (WIPO). It is a hierarchical system classifying inventions into technological groups and subgroups.

[12] The data on which the concordance table is based is provided by EUROSTAT in cooperation with KU Leven / Belgium.

[13] Note that this mapping matches IPC codes to NACE codes which represent only manufacturing industries. Excluding non-manufacturing patents does not represent a limit since I am focusing only on manufacturing firms which are typically the ones mostly exposed to trade shocks.

[14] Firm-level studies as Bloom et al. (2016) or Autor et al. (2020) use companies' names to combine patent data with firm-level datasets such as Compustat or Amadeus. Despite the numerous advantages of a firm-level analysis, this approach suffers from two limits. First,

Second, the IPC system allows us to identify green patents among the total population of patents. Particularly, I use the "Y02 classification" which was developed by the European Patent Office to complement the IPC and CPC classifications [15]. This tagging scheme provides a parallel code that classifies into groups and subgroups the "technologies or applications for mitigation or adaptation against climate change"[16]. For the purpose of the analysis, the "Y02 scheme" makes it possible to easily identify the distribution of green patents across industrial sectors once I combine it with the mapping scheme between technology classes and industries provided by PATSTAT. Among the subgroups belonging to the Y02 tagging code, I only exclude two classes: technologies for adaptation to climate change (class "Y02A") and nuclear energy technologies (class "Y02E30")[17]. Thus, I classify as green patents innovations in climate mitigation technologies which are inventions with a potential in reducing greenhouse gases emissions and improving climate sustainability [18].

Green patents identify not only clean innovation per se but also "enabling" technologies, which are typically high-tech inventions such as smart grids, intelligent systems or energy storage. Indeed, there is recent evidence that companies conducting green and climate mitigation R&D are also high-tech and their proportion is rising quickly among energy start-ups [Popp et al. (2020)]. The recent contribution by Bontadini and Vona (2020) suggests an important inter-linkage between green and high-tech innovations as their analysis reveals that production

patents granted to applicants that are not listed in the firm-level dataset are excluded from the final sample. Second, industry affiliation is typically given by the industry code listed in the firm-level dataset rather than defined by the type of the invention. Nevertheless, a firm may be an active innovator in multiple industries or firm's industry may also change over time. Coelli et al. (2022) infer firm's industry affiliation directly from patent data rather than from other sources. However, since industry affiliation is fixed and defined as the main industry where the firm has innovated in the past, it does not allow the firms to innovate in multiple sectors or in different industries over time.

[15] The Cooperative Patent Classification (CPC) is an extension of the IPC. It is jointly managed by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO) with the purpose of harmonising their patent classification practices.

[16] For a more detailed discussion on the classification of green and environment-related patents, see Veefkind et al. (2012)) and Haščič and Migotto (2015).

[17] After these two exclusion criteria, the broad classes of green inventions are: climate mitigation technologies related to buildings (e.g. housing, house appliances or related end-users applications, class "Y02B"); capture, storage, sequestration or disposal of greenhouse gases (class "Y02C"); information and communication technologies (class "Y02D"); related to energy generation, transmission or distribution (class "Y02E"); production or processing of goods (class "Y02P"); related to transportation (class "Y02T"); related to wastewater treatment or waste management (class "Y02W").

[18] Nuclear energy can reduce emissions but has other detrimental aspects and is not considered ecologically sound. I note that even if I include adaptation and nuclear technologies, the sample size of green patents does not increase significantly and the empirical results remain unchanged.

of green products is concentrated in high-tech industries.

Another advantage of patent data is that they are available with a long time series that allows to analyze long trends in patenting activity. PATSTAT keeps records of patents filed to the EPO office since 1978 [19]. For patents applied to other national offices, the database is even longer and it dates back since mid 60s. As conventional in the empirical innovation literature, I date patents by the earliest application year rather than considering the grant or publication date [20]. This is to better reflect the time when the innovation activity was carried out.

Patents applications are also a rich source of information regarding the applicants associated with the invention and the destination office of the application. It is possible to retrieve the name and residence country of the applicant and, in some cases, also the location of the innovation through the inventors' addresses. Since I group patents at the industry level, I do not encounter the limitation of identifying unique patent holders among patent records that frequently contain different names for the same applicant [21]. On the other hand, I exploit the information regarding the residence country of the applicant to group patents at the industry-country level. Moreover, PATSTAT gives information about the type of applicant, i.e. whether the applicant is a company, a university, a hospital, a governmental agency, a non-profit organization or an individual inventor. I restrict the patent sample to corporate patents (patents filed by private companies) since I am interested in studying market dynamics, particularly how firms respond in terms of innovation activity to a change in foreign import competition.

Nevertheless the previous key advantages, there are some limitation when using patent data to measure innovative activity. First, there also other ways to protect inventions as not all of them are patentable or patented [see Haščič and Migotto (2015)] [22]. Second, patents greatly vary in quality and economic values. This is particularly relevant when comparing patents internationally,

[19] The EPO was founded in late 1977.

[20] Usually, there is a lag of around two years between the earliest application date and the publication date.

[21] The problem typically occurs because of misspellings, abbreviations or variations in the applicants' names. These limitations are particularly relevant for firm-level studies. As an example, the IBM company can enter in a patent document as simply "IBM" or "International Business Machine" or with other abbreviations. Thus, for a large amount of data, it becomes challenging to manually identify unique company names. Autor et al. (2020) employs an algorithm based on internet search functions that is suitable to efficiently match different firm's names without sacrificing accuracy. Since 2011, PATSTAT, in collaboration with ECOOM (K.U LEUVEN), has elaborated its own automated algorithm to standardize the applicant original names into standardized names in order alleviate this problem.

[22] There are other aspects of technological change such as the "learning-by-doing" that is not necessarily embedded in new invention and is, therefore, not captured by patent data.

across patent offices that have different regimes regarding the granting process for a given innovation. While the first problem would potentially require the development a new comprehensive measure of innovation that is out the scope of this work, to cope with the second problem I only consider granted patents that have been filed to the EPO office [23]. Restricting to EPO patents has several advantages. First, the EPO office belongs to the group of the three main world patent offices together with the Japanese Patent Office (JPO) and the United States Patents and Trademark Office (USPTO). Patents filed and granted by the EPO office cover highly valuable inventions and are considered a method to control for patents' quality by the literature [24]. Second, focusing on patents filed to one patent office provides a standard measure of innovation that avoids to mistakenly confound idiosyncrasies across different administrative regimes with differences in the innovation activity [25]. Third, the focus of the analysis is to study the impact of increased import competition on the innovative activity of European firms. Thus, it is consistent to restrict to EPO patents since I suppose that companies are likely to protect their inventions from foreign imports firstly in their home market.

I aggregate the number of corporate patent applications by country/ sector and application year. Since I restrict to patents filed and granted in only one patent office (i.e., the EPO), it is not necessary to use "patent families" in order to identify identical inventions filed in multiple offices [26]. Thus, in order to quantify the number of unique inventions, I can simply count the number of patent applications for each country/sector. The only source of double counting that may arise is when the same patent is co-owned by firms from different countries. A typical example is when two companies with different residence countries cooperate on R&D and they jointly file the same patent application [27]. In this case

[23] Not all filed patents are granted. In general, to be granted, an invention has to be new and industrially applicable. Restricting to granted patents is an initial method to filter for quality.

[24] It is common in the literature to define "triadic" patents those that have been jointly granted by the three major patent offices, the EPO, the JPO and the USPTO. I choose to focus on patents grated by the EPO.

[25] It can happen, for example, that the same invention is covered by one patent in one patent office and by two or more in another office.

[26] Inflating the patent count typically occurs when a unique patent is filed in multiple offices because the applicant seeks protection in multiple countries and jurisdictions. In the literature, this issue is addressed by looking at "patent families", which group together all the subsequent patent applications protecting the same invention. Particularly, PATSTAT organizes patent applications that share the same initial priority application into the same patent family.

[27] In other words, if the same patent is co-owed by two different firms within the same country it is counted once, while if the two firms are from two different countries, the same patent is counted twice. I note that, in the sample, this last case is very infrequent as the sample size increases only negligibly when I count unique applications following the previous criteria as

I let the patent to be counted in every country the applicant belongs to.

An advantage of using PATSTAT is that I do not inflate the number of unique patent applications when I group by industry sectors [28]. This is possible by means of the weighting scheme included in the database that associates each patent to an industry/technical field. The weight is comprised between between 0 and 1 depending on relationship between an application and a industry/technical field. The total sum of weights for each patent is equal to one. Thus, by summing applications' weights by industries, I do not over count patents as, instead, it would result in case of counting as one the same patent in each industry. Moreover, the weights are measures of the closeness between a patent and an applicable industry. Thus, this measure of weighted patents count by industries improves accuracy and is preferable to a indiscriminate assignment of unique patents to multiple industries.

2.4.2 Chinese Trade Exposure

To measure trade exposure to Chinese imports, I use trade information sourced from the CEPII BACI database [29]. The database is built from data of UN Comtrade. It provides bilateral trade flows disaggrated at product level between any pairs of countries. I aggregate from six-digit HS product level to 2 or 3-digit NACE (Revision 2) industry level, thus matching the most disaggregated level that is available for patent data [30].

Following Bloom et al. (2016), I measure Chinese import exposure as the share of import values originating from China (M^{CN}) over total world import values (M^{World}) in each country-industry cell, i.e., $IMP^{CN} = M^{CN}/M^{World}$ [31]. Thus, the change in Chinese import share (ΔIMP^{CN}) is the measure of change

opposed to strictly assigning one patent to one country.

[28] If I count the same patent in every industry is associated with, I would risk to over count inventions with a wide range of industrial applications at the expenses of inventions associated with only one industry.

[29] Access to the database at: http://www.cepii.fr/cepii/en/bdd_modele/presentation.asp?id=37

[30] The 6-digit HS classification provided by CEPII BACI directly links to 6-digit CN codes, the European classification of goods. Through appropriate correspondance tables provided by EUROSTAT, I match CN product codes to 4-digit CPA 2008 classification codes, which, in turn , directly correspond to NACE Rev. 2 industry codes at all levels. Finally, I aggregate at 2 or 3-digit level of disaggregation.

[31] As an alternative meausre of import penetration, I try to normalize Chinese import on apparent consumption (domestic consuption less exports plus imports) using production data from Eurostat's prodcom database. However, this method is often not reliable (due to the integration of production and trade data) and it gives a large fraction of missing data in country-industry cells (due to missing information in production data for confidentiality reasons). Given these data limits, the normalization using world imports is preferred.

in trade exposure from China. I follow the same procedure to construct the instrumental variable, i.e. the industry-level import share in other OECD high-income countries.

2.4.3 Final Sample and Descriptive Evidence

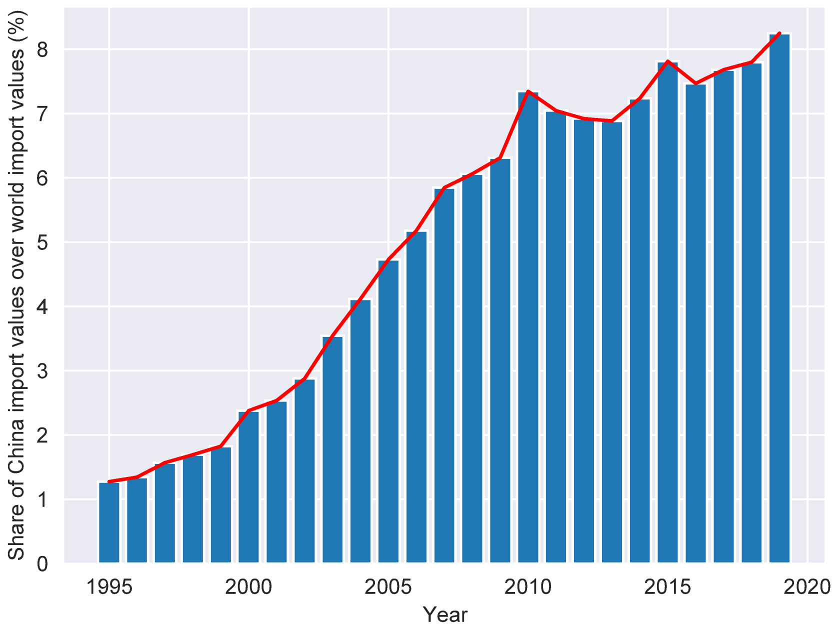
The final sample includes the top thirteen European countries for corporate patent applications (which jointly account for more than 90 percent of all patent applications filled by firms located in all European countries) [32]. This group of countries closely reflects the country selection used by Bloom et al. (2016) allowing for better comparability of the results. I collect patent data from 1978, but the main analysis and regressions are carried out on the period 1995-2015, which coincides on when the China trade shock occurred and on when bilateral trade data are available. Figure 2.2 shows that the China's share of all imports to the thirteen countries in the sample rose over time and ramped up after China accession to the WTO in 2001 expanding from about 1.2% in 1995 to 7.8% in 2015.

During the same period, there was an expansion of patent activity that was particularly pronounced towards green inventions. Figure 2.3 plots by year of patent application the number of green (panel A) and total (panel B) corporate patent applications in the top six European countries. The prevalence of green and total patents filled by German firms is remarkable but similar growth trends in patenting are observed for the other countries as well. The acceleration in green innovation is outstanding. Figure 2.4 plots the ratio of green over total number of patents (panel A) and the ratio of the green patent stock over total stock (panel B). The figure reveals a sharp rise in both ratios since the second half of the 1990s for both the sample of European countries and the United States. However, the aggregate trends mask important heterogeneity across sectors. Indeed, despite this evocative descriptive evidence, an econometric analysis combined with an appropriate identification strategy is needed to assess whether the rise in Chinese imports may have influenced innovation trends.

The final sample of patents (for the period 1978-2015) used in my analysis consists of 52874 green patents for total number of patents of 808090 which ac-

[32] The thirteen European countries are Austria, Switzerland, Germany, Denmark, Spain, Finland, France, United Kingdom, Ireland, Italy, Netherlands, Norway and Sweden. I do not limit to members of the European Union as I include also Switzerland, Norway and the United Kingdom (no longer EU member since 2020). Belgium and Luxembourg, despite a moderate fraction of patent applications, are excluded due limitations in trade data that is provided aggregated for the two countries until 1998.

FIG. 2.2: Share of all imports from China (over world imports) to 13 large European countries



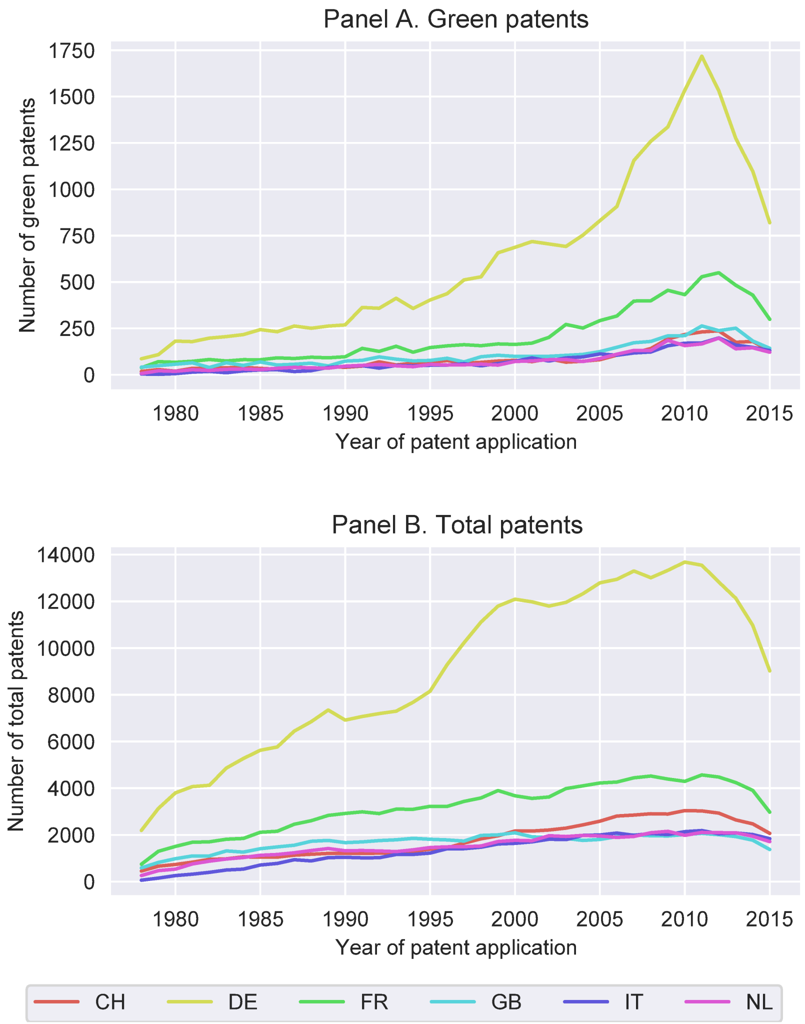
Notes: Calculated using UN Comtrade data from BACI dataset

count for about 90 percent of the raw patent extraction that I performed from the PATSTAT database [33]. I discussed above that I focus on large European countries and I do not consider patents as green those regarding adaptation and nuclear technologies (in any case, they only account for less than 8 percent of the raw patent extraction and their inclusion does not change the results).

Another selection criteria regards either the industries included in the analysis and how I aggregate them. First, I only focus on manufacturing industries as manufacturing firms are typically the ones exposed to trade shocks and to the relative increase in foreign import competition. Among the manufacturing industries, I focus on industries with a potential in innovation by excluding few sectors where there are no inventions (or a negligible number) in terms of either green or generic patents throughout the entire long time-series since 1978. Figure 2.5 plots the distribution of patents across NACE 2-digit sectors obtained from the full raw extraction (see the Appendix for a description of the NACE sectors). The figure shows that, historically, some sectors accounted for a very negligible fraction of (green and total) patents. These sectors are, thus, excluded from the

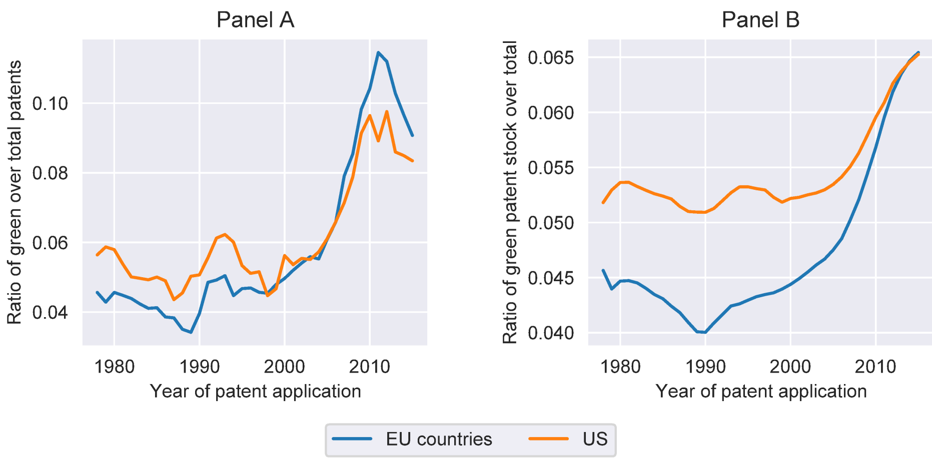
[33] I extract from PATSTAT all patent applications filled to the EPO office, that have been granted, applied by firms whose home country was an European country (including all EU countries and not only large EU countries) and for the period 1978-2018. Thus, the raw patent extraction gives 63139 unique green patents and a total of 900833 unique patents.

Fig. 2.3: Number of green and total patents by year in top 6 EU countries



Notes: Calculated using the PATSTAT dataset

FIG. 2.4: Ratio of green over total patents (panel A) and ratio of green patent stock over total patent stock (panel B) in 13 large EU countries and USA



Notes: Calculated using the PATSTAT dataset

analysis [34]. Second, I maximize the use of the data when aggregating by sector. In fact, not all patent information from PATSTAT share the same industry-level of disaggregation. For some sectors, patents can be disaggregated more granularly (at 3 or 4-digit), while, for others, the industry code associated with each patent is only at 2-digit. Thus, whenever it was possible, I exploited the more granular level of disaggregation at 3-digit codes [35]. Figure 2.6 plots the patent distribution across sectors of the final sample of patents. I therefore match these sectors with trade data that I consistently grouped with the same scheme.

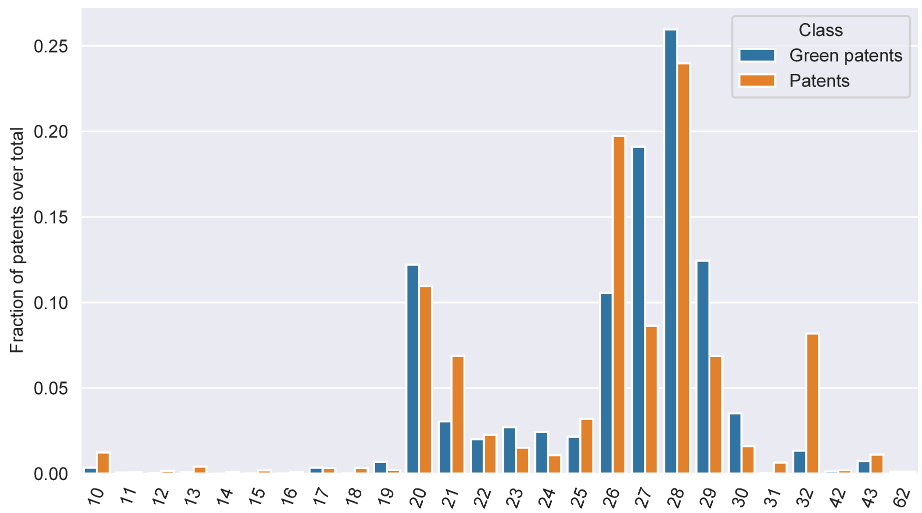
Finally, I support the argument that Chinese firms are less green-tech intensive than European firms by showing the descriptive evidence of Figure 2.7. The figure plots by 2-digit industry the average green knowledge stock (over total patent stock) accumulated until 2000 by Chinese firms as compared to the European average. Despite few exceptions, the average green knowledge stock in each sector is much higher than the Chinese average suggesting that, on average, European firms had a technological lead across sectors in terms of green innovation at the moment of China WTO accession [36].

[34] Sectors excluded are: "Food", "Beverages", "Tobacco", "Textile", "Wearing", "Leather", "Wood", "Paper", "Printing".

[35] In the final sample, I have a total of 13 NACE 2-digit sectors. For 6 of them (codes: 20, 25, 26, 27,28, 29), I have exploit the disaggregation at three digits. The remaining 7 sectors are kept at 2-digit as patents associated to these sectors cannot be disaggregated to a more granular level. The final number of sectors (2-digit plus 3-digit) is equal to 40.

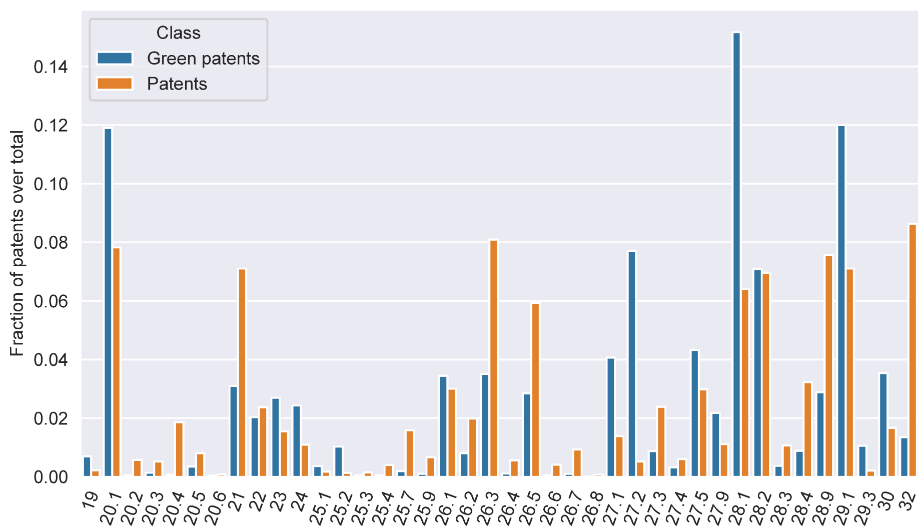
[36] The figure may even overestimate the Chinese green knowledge stock as I computed the Chinese average by sector considering all patents filed to every world office and without controlling for quality.

FIG. 2.5: Distribution of patents across NACE 2dig. sectors (full extraction)



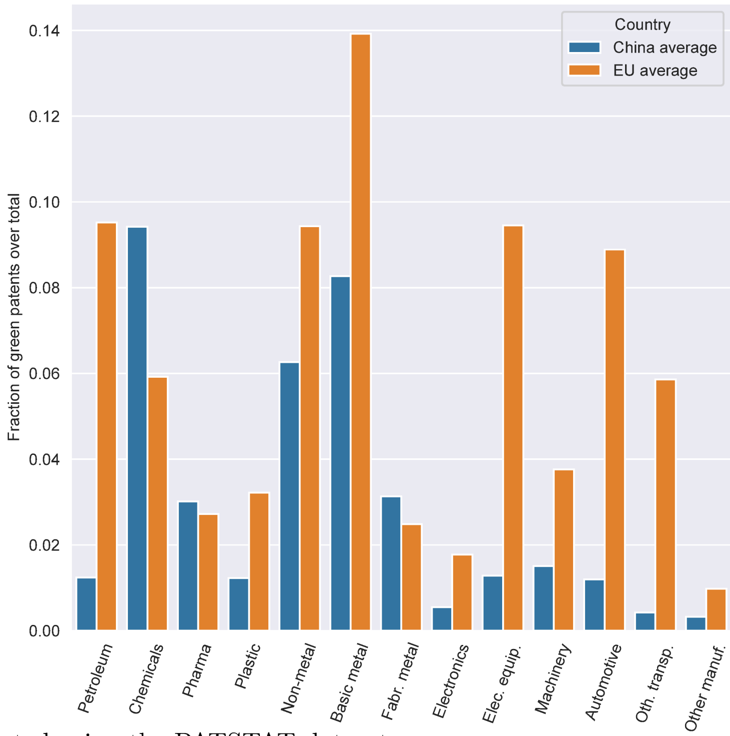
Notes: Calculated using the PATSTAT dataset

FIG. 2.6: Distribution of patents across NACE 2-3dig. sectors (final sample)



Notes: Calculated using the PATSTAT dataset

FIG. 2.7: China vs EU: average green knowledge stock by sector (1978-2000)



Notes: Calculated using the PATSTAT dataset.

Table 2.1 shows the mean, median and standard deviation of the main variables used in the econometric analysis, i.e. ΔK^g_{jn}, ΔK^t_{jn} and ΔIMP^{CN}_{jn}. The exposure period considered is 1995-2015 and the number of units (country-industry pairs) is equal to 516 [37]. The exact number of observations across regressions is conditioned on non-missing values in the dependent variables. The sample size is slightly smaller for the change in green patent stock as there are some units with both zero values in the stock at the beginning and the end of period. I also show in the same table other informative variables such as the raw difference in knowledge stock over 1995-2015 and its aggregate increase. This latter gives the number of patent applications filled over the period that is equal to 42440 green patents for a total 565146 patents.

[37] The number of units is slightly smaller than what I would obtain by multiplying the number of countries (13) with the number of sectors (40) as, for Ireland, patent data are limited to 37 sectors and, for Norway, to 39 sectors.

Tab. 2.1: Summary Statistics

	Mean	Median	St. dev.	N
Green patent stock:				
$K^g_{jn,2015} - K^g_{jn,1995}$	82.2	11.4	258	516
$\sum_{jn}(K^g_{jn,2015} - K^g_{jn,1995})$	42440			
ΔK^g_{jn}	.521	.4	.474	7258
Total patent stock:				
$K^t_{jn,2015} - K^t_{jn,1995}$	1095	233	2656	516
$\sum_{jn}(K^t_{jn,2015} - K^t_{jn,1995})$	565146			
ΔK^t_{jn}	.364	.311	.257	8217
Chinese import share:				
$IMP^{CN}_{jn,2015} - IMP^{CN}_{jn,1995}$	.0771	.0549	.0838	516
ΔIMP^{CN}_{jn}	.0207	.0105	.0413	8256
N of countries:	13			
Number of industries:	40			
Number of units:	516			
Years:	1995-2015			

Notes: Patent and trade data are available for 40 industries for 11 countries. For Ireland, patent data are limited to 37 industries, while for Norway to 39 industries. Countries are: AT, CH, DE, DK, ES, FI , FR, GB, IE, IT, NL, NO and SE. NACE Rev. 2 industries aggregated at the 2-digit are: 19, 21, 22, 23, 24, 30, 32; industries available at the 3-digit level of disaggregation are 20, 25, 26, 27, 28, 29. ΔK_{jn} is the 5-year proportional change defined as $\Delta K_{jn} = (K_{jn,t} - K_{jn,t-5})/(0.5K_{jn,t} + 0.5K_{jn,t-5})$ (g indicates green patents, t indicates generic patents). ΔIMP^{CN}_{jn} is the change in the share of the import value (M) originating from China: $\Delta IMP^{CN}_{jn} = (M^{CN}/M^{World})_{jn,t} - (M^{CN})/M^{Wolrd})_{jn,t-5}$. Patent data are from the PATSTAT dataset. Trade data are sourced from BACI dataset.

2.5 Results

2.5.1 Baseline Estimates

Following equation (2.1), (2.2) and (2.3), I proceed by estimating the impact of rising Chinese import on the technical change at the country-industry level. Table 2.2 presents the baseline results. All specifications consists of overlapping long differences that control for country-industry fixed effects. All columns include a full set of country dummies interacted with time dummies in order to absorb country-specific macro shocks. Columns (1) to (2) show the results regarding the growth in green patent stock at the country-industry level. In columns (3) to (4), I report the results obtained by changing the dependent variable with total patent stock. Columns (5) to (6) corresponds to equation (2.3), where I difference the estimated coefficients of the import competition impact on green and total innovation outcomes in order to better assess the direction of technical change. For each empirical specification I report side-by-side the OLS and 2SLS estimates. As described above, I instrument the industry import exposure variable ΔIMP_{jn}^{CN} with the change in industry import share in other high income countries $\Delta IMP_{j,other}^{CN}$. In all specifications, the estimated standard errors are clustered by country-industry unit.

Panel A of Table 2.2 includes no additional covariates beyond the change in import share and country-year dummies. The coefficient of Chinese import exposure on growth of patent stocks is positive and significant in all specifications (both OLS and 2SLS models) pointing to a positive effect of China import competition on the innovation activity of European firms. Both OLS and 2SLS coefficients on green patent stock in columns (1) and (2) are three times larger than the coefficients on total patenting in columns (3) and (4). Moreover, the difference between the two coefficients is remarkable and significant as reported in columns (5) and (6) for the OLS and 2SLS, respectively. This allows us to infer an additional important result regarding the direction of technical change and product switching. Import competition from a low-wage country as China appeared to induce a faster growth rate in green rather than total patenting at the aggregate industry level. By using $\Delta K_{jn}^{g} - \Delta K_{jn}^{t}$ as dependent variable, not only I isolate the component of the import competition effect on green growth that outweighs total patent growth, but I also purify from wider innovation trends correlated with both green innovation and import flows.

Tab. 2.2: Baseline results

Panel A: Baseline results						
Dep. Var.	ΔK^g_{jn}		ΔK^t_{jn}		$\Delta K^g_{jn} - \Delta K^t_{jn}$	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
ΔIMP^{CN}_{jn}	0.942^{***}	2.850^{***}	0.335^{**}	0.992^{***}	0.674^{**}	1.895^{***}
	(0.318)	(0.722)	(0.132)	(0.350)	(0.271)	(0.642)
KP F-stat		162.908		191.531		162.908
Ctry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N of units	475	475	516	516	475	475
Obs.	7258	7258	8217	8217	7258	7258
Panel B: Controlling for pre-characteristics						
Dep. Var.	ΔK^g_{jn}		ΔK^t_{jn}		$\Delta K^g_{jn} - \Delta K^t_{jn}$	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
ΔIMP^{CN}_{jn}	0.830^{***}	2.533^{***}	0.328^{**}	0.902^{***}	0.569^{**}	1.632^{***}
	(0.305)	(0.703)	(0.129)	(0.344)	(0.259)	(0.628)
$\ln(K^g_{pre})_{jn}$	-0.074^{***}	-0.069^{***}			-0.073^{***}	-0.070^{***}
	(0.012)	(0.012)			(0.011)	(0.012)
$\ln(K^t_{pre})_{jn}$			-0.026^{***}	-0.026^{***}	0.014	0.013
			(0.006)	(0.006)	(0.009)	(0.009)
KP F-stat		161.837		190.996		163.180
Ctry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N of units	475	475	516	516	475	475
Obs.	7258	7258	8217	8217	7258	7258

Notes: Standard errors (in parentheses) are clustered at the industry level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

The second-stage estimates are uniformly larger than OLS counterparts [38]. The IV strategy results to be useful to correct for simultaneity and measurement errors which both, if not accounted for, would cause a downward bias on the OLS estimates. The correlation between industry demand side shocks and Chinese imports (that both are likely to influence innovation) does not seem to drive the results as there is no evidence of upward bias for OLS [39].

In panel B of Table 2.2 I show the results when adding industry pre-period knowledge stocks (i.e., cumulative patent counts from 1978 to 1994). The coefficients do not vary significantly when I control for the (past) level of innovation at the country-industry level. The negative (and significant) 2SLS coefficients on the pre-sample stock variables seem to suggest that there was a catching up trend in both green (column 2) and total (column 4) innovation for those sectors with lower levels of past patenting activity in green and generic innovation, respectively. More on the catching up of lagging sectors will be disclosed when later I will include the lagged level of technology stock and the industry measure of distance to the frontier.

2.5.2 Robustness to Industry Trends

The identification strategy relies first on isolating the supply-driven component of Chinese imports through the use of an appropriate instrumental variable, identified by the Chinese import exposure in other high high-income countries. I proceed by addressing the second econometric concern: the potential correlation between sectoral innovation trends and the rise in foreign import competition that might contaminate the estimates. Table 2.3 shows the robustness of the baseline results to including industry dummies that absorb any patenting long run trend at the industry level. In panel A I include 2-digit wide industry fixed effects (13 sectors) in the growth baseline specifications. In panel B I control for trends at the most detailed industry level available (40 sectors). In panel C I interact the full set of detailed industry dummies with country dummies by accounting for any country-industry specific trends. The primary source of identification becomes therefore the within-country-industry changes over time in import exposure and patents accumulation. All columns report the results of the 2SLS estimation strategy.

Estimates confirm the positive relationship between Chinese import compe-

[38] The first-stage F-statistics are large confirming the relevance of the instrument.

[39] For an extensive discussion regarding the direction of bias on OLS of trade variables see Autor et al. (2013), Autor et al. (2014) and Bloom et al. (2016).

tition and the growth in green patent stock when including industry trends, as shown in column (1) of each panel in Table 2.3. Adding sector dummies reduces the magnitude of the coefficients on import competition in all specifications. Thus, the growth in imports partially reflect secular innovation trends. The point estimates remain positive and with comparable magnitudes across all panels even if the results are not robust to all set of industry dummies. Adding detailed industry trends that are not country-specific (panel B) tend to exacerbate any attenuation bias and to inflate excessively the standard errors due to the high variation in the effect across European sectors. On the other hand, when I control for between-country differences in industry trends in panel C, the coefficient increases and becomes significant again at the 10% level. This seems to suggest that country-specific industry trends are not only important to better isolate the impact of trade variables, but also to absorb the excessive variation in the estimates across European industries.

The impact of import competition on total innovation at the industry level is instead more ambiguous as shown column (2) of Table 2.3, i.e. when I use the growth in total knowledge stock as dependent variable. The coefficient estimated is only robust to the less conservative set of industry dummies (wide industry fixed at 2-digit level), while it is no longer significant (and it also becomes negative) when I control for detailed industry and country-industry trends.

Consequently, the results reported Column (3) of Table 2.3 show that increased import competition caused an acceleration of green patent accumulation with respect to generic inventions. The coefficients on the difference between the import competition effect on green and total patent growth are positive and significant at 10% or greater across all panels. The largest magnitude and precision in the estimates are in panel C that include country-industry trends. Differentiating the two growth rate is useful to purge green innovation growth from wider innovation trends. This explains why the estimates using $\Delta K^g_{jn} - \Delta K^t_{jn}$ as dependent variable are in general more stable, with or without industry trends. Thus, I argue that the results regarding the impact of import competition on green innovation are robust even after removing the spurious correlation between import shocks and wide-long trends in innovation.

The definition given in section 2.3 of ΔK_{jn} as proportional scaling change approximates very closely a log change [40]. By approximating, I can therefore interpret the coefficients as semi-elasticities. Considering the net impact on green innovation (i.e., after differencing away the effect on total innovation), the magni-

[40]The correlation between ΔK_{jn} and $\Delta ln K_{jn}$ in the data is equal to 0.97.

TAB. 2.3: Controlling for Industry Trends

Panel A: Include Industry Trends (13 sector dummies)			
Dep. Var.	ΔK^g_{jn}	ΔK^t_{jn}	$\Delta K^g_{jn} - \Delta K^t_{jn}$
	(1)	(2)	(3)
	2SLS	2SLS	2SLS
ΔIMP^{CN}_{jn}	2.115^{**}	0.913^{**}	1.437^{*}
	(0.855)	(0.424)	(0.766)
KP F-stat	104.947	127.287	104.947
Ctry-year FE	Yes	Yes	Yes
Ind. Trends (Nace 2dig)	Yes	Yes	Yes
N of units	475	516	475
Obs.	7258	8217	7258
Panel B: Include Industry Trends (40 sector dummies)			
Dep. Var.	ΔK^g_{jn}	ΔK^t_{jn}	$\Delta K^g_{jn} - \Delta K^t_{jn}$
	(1)	(2)	(3)
	2SLS	2SLS	2SLS
ΔIMP^{CN}_{jn}	1.301	-0.242	1.717^{*}
	(0.974)	(0.478)	(0.909)
KP F-stat	42.850	50.978	42.850
Ctry-year FE	Yes	Yes	Yes
Ind. Trends (Nace 3dig)	Yes	Yes	Yes
N of units	475	516	475
Obs.	7258	8217	7258
Panel C: Include a full set of Country-Industry Trends			
Dep. Var.	ΔK^g_{jn}	ΔK^t_{jn}	$\Delta K^g_{jn} - \Delta K^t_{jn}$
	(1)	(2)	(3)
	2SLS	2SLS	2SLS
ΔIMP^{CN}_{jn}	1.614^{*}	-0.281	1.994^{**}
	(0.889)	(0.469)	(0.802)
KP F-stat	42.033	51.037	42.033
Ctry-year FE	Yes	Yes	Yes
Ctry-Ind. Trends	Yes	Yes	Yes
N of units	475	516	475
Obs.	7258	8217	7258

Notes: Standard errors (in parentheses) are clustered at the industry level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

tude of the coefficient ranges between 1.89 in the baseline estimations (column 6 of Table 2.2 panel A) to 1.99 in the specification controlling for country-industry trends (column 3 of Table 2.3 panel C). This implies that a one point increase in Chinese import share causes about 1.9 percent increase in the green knowledge stock with respect of total innovation of an industry over a period of five years. The data shows that over the period 1995-2015 the mean increase in the country-industry specific import share from China was 2 percentage points (mean of ΔIMP_{jn}^{CN} in Table 2.1). The results suggest that the observed green knowledge stock increased by almost 4% due to Chinese import competition.

The above results are in line with the directed escape-competition hypothesis. The positive impact of import competition from China is specifically on green innovation, while the overall volume of generic inventions did not increase with greater trade exposure. The results complement those from Bloom et al. (2016) that find that patenting rose within firms who were more exposed to increased China import competition. Even if Bloom et al. (2016) provide some evidence on product and industry switching, nothing is said about whether firms switched to more or less technologically advanced products. The results shed new light on the direction of technical change at the industry level. I find that only the production of green patents (and not total innovation) increased in industries with a greater increase in import competition. This evidence suggests that European firms directed innovation towards greener products in order to better escape competition from a low-wage country such as China.

2.5.3 Heterogeneity

A second purpose of my analysis is to investigate potential heterogeneity in the effect of import competition across industries. In this section, I only consider green innovation growth since the above results show that import competition effect is not robust for total patent growth. I examine whether the effect of import competition varies by interacting the trade variable with the lagged industry technology stock (Table 2.4) and with the measure of distance to the frontier (Table 2.5). Only 2SLS estimates are reported in the tables.

All columns in Table 2.4 show that low-tech industries (as indicated by a low level of lagged (log) green stock) display a faster rate of green and total patent accumulation. The catching up dynamics of industries that lag behind in terms of green innovation is confirmed in columns (5) and (6), when I use the net green knowledge growth out of total growth as dependent variable. Most importantly, the interaction coefficient between Chinese imports and lagged knowledge stock is

Tab. 2.4: Interaction with lagged technology stock

	ΔK^g_{jn}		ΔK^t_{jn}		$\Delta K^g_{jn} - \Delta K^t_{jn}$	
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
ΔIMP^{CN}_{jn}	2.120**	7.329***	-0.002	0.533	1.708***	6.830***
	(0.831)	(2.571)	(0.424)	(2.206)	(0.609)	(2.383)
$ln(K^g)_{jn,t-5}$	-0.536***	-0.464***			-0.061***	-0.424***
	(0.048)	(0.054)			(0.009)	(0.049)
$\Delta IMP^{CN}_{jn} \times ln(K^g)_{jn,t-5}$		-1.969***				-1.655***
		(0.680)				(0.634)
$ln(K^t)_{jn,t-5}$			-0.432***	-0.427***		
			(0.041)	(0.042)		
$\Delta IMP^{CN}_{jn} \times ln(K^t)_{jn,t-5}$				-0.098		
				(0.333)		
Ctry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ctry-ind. trends	Yes	Yes	Yes	Yes	Yes	Yes
KP F-stat:						
ΔIMP^{CN}_{jn}	42.540	26.260	51.440	29.730	162.660	26.260
$\Delta IMP^{CN}_{jn} \times ln(K)_{jn,t-5}$		24.110		26.340		24.110
N of units	475	475	516	516	475	475
Obs.	7258	7258	8217	8217	7258	7258

Notes: Standard errors (in parentheses) are clustered at the industry level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

negative and significant at 1% in all specifications. This suggests that the impact of Chinese import competition on green patents growth is greater in low-tech country-industry units.

Similar results are obtained when I interact import competition with the industry level measure of distance to the green-tech frontier. Table 2.5 shows that the lagged industry-level distance ratio variable D_{jn} is negative and significant in all columns. Recalling that D_{jn} is larger for industries closer to the frontier, the negative coefficient on D_{jn} suggests that industries far from frontier sector experience, on average, a faster technical change. Thus, there seems to be evidence of convergence in green technology within sectors. When I interact the trade variable with the distance variable, the coefficient on the interaction term is negative and significant implying that green innovation grew faster in industries relatively far from the green-tech frontier in response to increased Chinese imports. Moreover, the effect (i.e. the coefficient on the linear ΔIMP^{CN}_{jn} plus the interaction effect with $D_{jn,t-5}$) decreases in magnitude and becomes close to zero for frontier industries [columns 2 and 4]. Consequently, the rate of technical change is faster in country-industries far from the frontier. This seems to support my hypothesis that when the average firm competes more directly with low-tech goods, it has

TAB. 2.5: Interaction with distance from the frontier

	ΔK^{g}_{jn}		$\Delta K^{g}_{jn} - \Delta K^{t}_{jn}$	
	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS
ΔIMP^{CN}_{jn}	2.235***	4.129***	2.029***	4.482***
	(0.750)	(1.166)	(0.552)	(1.148)
$D_{jn,t-5}$	-1.023***	-0.936***	-0.588***	-0.945***
	(0.066)	(0.076)	(0.044)	(0.069)
$\Delta IMP^{CN}_{jn} \times D_{jn,t-5}$		-4.115**		-3.323*
		(1.826)		(1.725)
Ctry-year FE	Yes	Yes	Yes	Yes
Ctry-ind. trends	Yes	Yes	Yes	Yes
KP F-stat				
ΔIMP^{CN}_{jn}	41.703	22.130	163.306	22.130
$\Delta IMP^{CN}_{jn} \times ln(K)_{jn,t-5}$		22.740		22.740
N of units	475	475	475	475
Obs.	7243	7243	7243	7243

Notes: Standard errors (in parentheses) are clustered at the industry level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

stronger escape-competition incentives. Green patent growth is instead slower in high-tech country-industries as the average firm has little incentives to innovate more in response to import competition given its technology lead over low-tech competitors. These results are in line with my "reverse" distance to the frontier argument inspired by the theory of Aghion et al. (2005).

A final point that is worth stressing is that the industry-level estimates capture both the within and between firm effect of increased Chinese trade exposure. In a nutshell, the faster rate of technical change in low-tech industries may be attributed to the within firm response in terms of innovations to more competition and to the within sector reallocation of the innovative activity from low-tech firms to high-tech firms. One advantage of the approach is that by aggregating at the industry level I prevent the bias of selecting only non-exit firms that are likely to be technologically improving regardless the China trade shock. This dynamic selection bias clearly arises in firm-level studies that limit the sample to a cohort of firms alive during the entire period. Instead, the industry-level estimated impact of import competition includes the effects attributable to the exit of weaker firms, the innovation response of surviving firms and the entries of new

TAB. 2.6: Double Differences

	$\Delta\Delta K^{g}_{jn}$	$\Delta\Delta K^{t}_{jn}$	$\Delta\Delta K^{g}_{jn} - \Delta\Delta K^{t}_{jn}$
	(1)	(2)	(3)
	2SLS	2SLS	2SLS
$\Delta\Delta IMP^{CN}_{jn}$	1.792**	-0.570	2.172***
	(0.874)	(0.576)	(0.823)
KP F-stat	38.907	47.102	38.907
Ctry-year FE	Yes	Yes	Yes
N of units	466	516	466
Obs.	4892	5637	4892

Notes: Standard errors (in parentheses) are clustered at the industry level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

innovators. The drawback is that I cannot disentangle which dynamics prevail: whether the acceleration in the industry-average innovation growth is explained more by the reallocation component (shifts in innovation activity from low-tech firms towards high-tech firms within industry) or by the within technological upgrading of low-tech firms. The methodology proposed by Bloom et al. (2016) is suitable to disentangle the aggregate technical change in the within and between firm components. More research on this is ultimately needed to complement the above findings with a firm-level methodology.

2.6 Robustness Checks

Another way to eliminate the influence of country-industry trend is by double differencing equation 2.7. This approach sweeps away the country-industry fixed effects (i.e., θ_{jn}) I added to the growth specifications. Table 2.6 shows that the results obtained are analogous to those presented in Panel C of Table 2.3, i.e. when including a full set of country-industry trends to the long-differenced specifications. The magnitudes of the coefficients remain substantially unchanged confirming the positive impact of Chinese import competition on the growth of green patent stock (column 1), even after controlling for the growth in total patent stock (column 3) and suggesting that there is no significant effect on total generic innovation (column 2). The coefficients in Table 2.6 are also more precisely estimated.

After eliminating the influence of country-industry trends, another potential

Tab. 2.7: Falsification Test: pre-period 1978 - 1990

	ΔK^g_{jn}	ΔK^t_{jn}	$\Delta K^g_{jn} - \Delta K^t_{jn}$
	(1)	(2)	(3)
	2SLS	2SLS	2SLS
ΔIMP^{CN}_{jn}	-0.686	-0.234	0.277
	(1.326)	(0.927)	(1.432)
KP F-stat	56.594	71.666	56.594
Ctry-year FE	Yes	Yes	Yes
Ctry-ind. trends	Yes	Yes	Yes
N of units	332	492	332
Obs.	2406	3763	2406

Notes: Standard errors (in parentheses) are clustered at the industry level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

concern is that industries exposed to the China trade shock always had higher growth rates in patenting activity compared to other industries, regardless the trade shock. In order to assess whether industry pre-trends are driving my results, I perform a falsification test to compare the main estimates of Table 2.3 with those obtained from regressions in the pre-period. In other words, I regress the change in patent stocks during the period before the China trade shock (1978-1990) on the future change in Chinese import shares (using the period 1995- 2007) [41]. If the coefficients estimated in the test turn out to be insignificant and close to zero, this suggests that the industry pre-trends are not driving the results obtained for the exposure period 1995-2015. As shown in Table 2.7, the coefficients estimated drop in magnitude and are no longer significant for each dependent variable considered, i.e. green patent stock growth (column 1), total patent stock growth (column 2) and net green patent stock growth (column 3). This suggests that there are no pre-trends in patenting.

Table 2.8 reports the results of robustness tests using alternative empirical specifications. Column (1) shows the coefficient estimated by regressing the net green patent stock growth on Chinese imports, but using an alternative instrumental variable: the change in the Chinese import share for the same group of extra-EU OECD countries but excluding the United States. The exclusion of the U.S., whose industry demand shocks are potentially correlated with those in

[41] The empirical specifications are analogous to equation 2.7), i.e. 5-year long differences including country-industry trends. I present the results from 2SLS estimation.

the European countries, should strengthen the identifying assumption of demand shocks to be uncorrelated across countries. Even after changing the instrument, the coefficient remains substantially unchanged, slightly larger in magnitude with respect to the one shown in in column (3) of Table 2.3 Panel C (i.e., obtained by using the baseline instrumental variable). In column (2), I present the results obtained by using a one-year difference operator, instead of considering 5-year long differences. The coefficient remains stable even though less precisely estimated. Column (3) reports the estimate using the change (5-year long) in the log-transformed ratio of green patent stock over total patent stock $\Delta \ln(\frac{K^g}{K^t}_{jn})$ as dependent variable in place of the approximation I used throughout the empirical analysis [42]. The coefficient (1.74) does not differ substantially from the one found using $\Delta K^g_{jn} - \Delta K^t_{jn}$ as dependent variable [43].

Tab. 2.8: Alternative Empirical Specifications

	$\Delta K^g_{jn} - \Delta K^t_{jn}$		$\Delta \ln(\frac{K^g}{K^t})_{jn}$	$\ln(\frac{K^g}{K^t})_{jnt}$	K^g_{jnt}	
	(1) Alternative IV	(2) 1-year FD	(3) Log Change	(4) Levels	(5) PPML	(6) PPML
ΔIMP^{CN}_{jn}	2.084**		1.746**			
	(0.888)		(0.767)			
$\Delta_{1y} IMP^{CN}_{jn}$		1.927*				
		(1.010)				
IMP^{CN}_{jnt}				1.215*	1.401***	0.955*
				(0.722)	(0.318)	(0.555)
$\ln(K^g_{pre})_{jn}$						0.481***
						(0.099)
$\ln(K^t_{pre})_{jn}$						0.158*
						(0.094)
Ctry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE				No	No	Yes
Ctry-ind. FE				Yes	Yes	No
Ctry-ind. trends	Yes	Yes	Yes	Yes	No	No
KP F-stat	32.110	40.237	41.779	35.798		
N of units	475	475	461	475	475	516
Obs.	7258	8888	6910	9281	9975	10836

Notes: Standard errors (in parentheses) are clustered at the industry level. * denotes significance at 10%. ** denotes significance at 5%. *** denotes significance at 1%.

[42] Using a log-transformed ratio is equivalent to the difference between the logarithm of numerator minus the logarithm of the denominator of the ratio. Thus, the economic interpretation of the coefficient does not change: I am still estimating the impact on the net growth rate of green patent stock over total patent stock (approximated as log change in this case).

[43] The sample size is a slightly smaller when using the log-transformed ratio due some zero values in the dependent variable at the beginning of a period.

As robustness check, I also consider specifications in levels rather than differenced equations. In column (4) of Table 2.8, I report the results of regressing the log-transformed ratio of green patent stock over total patent stock on Chinese import shares, including fixed effects and country-industry trends (country-industry dummies interacted with the time variable). The coefficient remains positive with the effect around 1.21 that is slightly smaller in magnitude and less significant than the long-differenced results. Finally, in order to deal with zero values in the dependent variable, I employ a Poisson Pseudo Maximum Likelihood (PPML) estimator and express the dependent variable in levels as the green patent stock. This approach allows to avoid sample selection bias and to also include zero values in the dependent variable. In column (5) I control for fixed effects at the country-industry level, while in column (6) I show the results from controlling for fixed effects by including pre-sample patent stocks and industry fixed effects [44]. In both cases, the coefficient on Chinese import shares remains positive and significant even if the magnitude of the effect is slightly smaller than those obtained from the baseline estimations.

2.7 Conclusion

This chapter studies the impact of trade on within-industry technical change in Europe. I focus on the China trade boom which constitutes the most relevant trade shock from a low-wage country in the recent history. This helps evaluating the impact of increased foreign import competition on Northern technical change which is still a debated issue in the literature. To do so, I use patent data to proxy industry-level innovation activity of thirteen European countries and trade data to measure the increased competitive pressure from China.

The results show no increase in total generic innovation activities in industries more exposed to rising Chinese imports. However, I find the effect to be specifically on green innovation as more exposed industries showed a faster innovation rate in green inventions. The evidence that European firms directed innovation towards green inventions in response to rising import competition from China is interpreted in light of the escape-competition theory by Aghion et al. (2005). My findings are also in line with those found by Bernard et al. (2006) on the reallocation towards capital-intensive activities and product switching across US manufactures due to industry trade exposure to low-wage countries.

[44]The regression reported in column (6) avoid dropping singletons and exploit all the observations in my sample.

The results appear to be robust to econometric issues such as the endogeneity of trade exposure and to confounding factors as industry patenting trends. Interestingly, the effect of increased import competition is heterogeneous and particularly strong in industries far from the technological frontier. One possible reason is that the industry-aggregate estimates capture both the within-firm technology upgrading and the reallocation effect of innovative activity from low-tech to high-tech firms. Unfortunately, an industry-level analysis does not allow to disentangle between the within and between firm effects. A firm-level analysis as the one proposed by Bloom et al. (2016) is ultimately needed to assess whether the reallocation effect prevailed on within firm technical change. Nevertheless, my results complement those found by Bloom et al. (2016) by revealing new evidence on the direction of technical change and pointing to a potential positive impact of China trade on the technological upgrading towards green technologies.

A further extension of this work could be taken in the direction of the literature on the environment and directed-technical change [Acemoglu et al. (2012), Aghion et al. (2016)]. Additional investigations should be indeed carried out in order to include in the analysis also the effects of environmental policies and energy prices which have been shown by literature to matter for green innovation. To conclude, this chapter provides a fruitful starting point to study the interplay between trade and green innovation.

2.A Appendix

Tab. 2.9: NACE Sector Description

NACE 2 digit code	NACE Sector Description
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
42	Construction
43	Other Construction
62	Information Service

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