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Institutional settings and financing green innovation☆

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A B S T R A C T

The sheer scale of the current environmental challenge underscores the need for successful generation and application of environmentally sustainable innovations. At the same time, there has been growing interest in how national institutional contexts interact with the financial ecosystem, corporate governance, and firm behaviour. Bringing these topics together, we theoretically address and empirically evaluate the institutional and financial conditions under which green innovation and application occur. Using a novel sample of 53 countries over a twenty-one-year period, we show that green innovation is more likely to occur in Liberal Market Economies, a crucial feature of which is the heavier reliance by firms on markets to obtain their finance. However, we also show that this innovation is applied more frequently in economies with a higher degree of State coordination and where high short-term returns are less in demand. Given national institutional contexts are persistent, our results highlight that extensive regulatory intervention is likely required to develop green economies.

1. Introduction

This paper focuses on *environmentally sustainable innovation* ("green innovation"), or *eco-innovation* (Franceschini et al., 2016), and assesses the impact of institutions, including financial systems, on the generation and application (implementation) of such innovation. The importance of these questions has become increasingly apparent given ongoing concerns related to quickly rising global

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temperatures, record atmospheric levels of greenhouse gases (Blunden et al., 2023), and substantial differences in countries' progress towards the 2050 carbon neutrality targets (see, for example, the Leaders' Summit on Climate, 2021).[1] Given reaching 'net-zero' requires both the replacement of fossil-fuel-derived energy with renewables, and the capture and storage of any residual emissions, the further development and widespread adoption of green technologies is essential. Our work brings together the literature on green innovation, institutional settings, and finance, showing that national institutional contexts and the financial system are key for determining the level of green innovation and the extent to which technologies are employed.

An extensive body of literature already focuses on the need for organisations, and in particular, businesses, to move onto more sustainable trajectories in how they manage their activities, insert themselves in global value chains and markets, and, indeed, what enables and constrains this (Shevchenko et al., 2016; Chowdhury et al., 2020). At the same time, literature is emerging on the role of the financial sector as an effective coordination mechanism that promotes sustainable development through new financial instruments and policies, collectively known as "green finance" (Sachs et al., 2019; Dikau & Volz, 2020; Chowdhury et al., 2020). There is much evidence that the design of the financial system and how it is regulated impacts the nature of economic activity and the relative mix of an economy (Thakor, 1996). It could be argued that the most efficient (and lightly regulated) financial systems are the best equipped to assess risks (for example, around stranded assets; see Rajan, 2006) and capitalise on new opportunities opened by technological advances, including green innovations. However, there is also evidence that in mature liberal market settings, institutional investors have a very mixed track record in taking climate risks into account during their investment decisions, reflecting flawed risk assessment models (Silver, 2017). This might suggest that the regulatory context and associated range of policy options are critical to successfully developing "greener economies" (Shimbar, 2021; Yang et al., 2022).

To understand how institutions affect differences in countries' ability to develop and employ green innovation, we resort to the comparative institutional literature, which both compares and contrasts national-level institutional arrangements, financial systems, corporate governance, and firm-level outcomes (Zhu et al., 2020; Leung et al., 2018; Simintzi et al., 2015; Cao et al., 2019; Harjoto et al., 2020; Li et al., 2017). In particular, an extensive Varieties of Capitalism (VOC)-based literature on innovation suggests that Liberal Market Economies (LMEs) have advantages in terms of radical innovation and the patenting of advances, and more Coordinated Market Economies (CMEs) in incremental innovation-based manufacturing (Dilli et al., 2018: Hall, 2018; Hall & Soskice, 2001: Allen, 2013; Mariotti and Marzano, 2019).

In this paper, we newly extend this logic to green innovation. Adopting a VOC lens, we hypothesise that economies closer to the Liberal Market end of the spectrum will likely generate more green innovation than coordinated alternatives. Most importantly, we expand substantially the work of the extant literature by analysing the application of green innovation within these institutional contexts. In doing so, we also posit that the factors that make LMEs successful generators of green innovation, including easier access to finance, may relatively impede their more extensive application of green innovation. We argue that, unlike patent development, the application of green technologies in organisational practices typically has high roll-out costs and longer investment timelines, even though it also delivers more stable revenue flows (c.f. Doh et al., 2021; Allen et al., 2021; Wood, 2018). The latter might be better served by bank-based financial systems (Allen et al., 2021). For instance, this may occur because of the greater demand for higher short-term returns characterising LME, which may deter the incurring of large sunk costs associated with new technologies, such as carbon sequestration.

Our empirical analysis tries to disentangle generation and application of green innovation. Hence we firstly test the effect on generation of innovation that goes beyond more crude measures as patents and secondly the implementation of those technologies. To do this we draw on a large and novel dataset for a sample of 53 countries from 2000 to 2020. We measure green innovation using a set of variables, including domestic patents attached to environment-related technologies and long-term trackers of countries' relative advantage in environment-related technologies. These measures are collected from the "green" section of the OECD Patent Statistics and Environmental Indicators, constituting probably one of the most comprehensive publicly available datasets on patents and innovation – widely used by academics and policymakers researching developments in these areas. To identify the application of such innovation, instead, we follow previous work on environmental sustainability (see, e.g., Andreou & Kellard, 2021; Almeida et al., 2017) suggesting that the implementation of green innovation can be partially evidenced via renewable energy consumption and a reduction in greenhouse gas emissions, using OECD Statistics and several other macroeconomic datasets to gather data on these variables. Following developments in the VOC literature (Witt & Jackson, 2016; Amable, 2003), we then match patent data with a broad range of institutional and financial indicators and use a principal component analysis (PCA) to shrink and orthogonalise the regression parameters with minimal loss of information. This parameter-reduction technique is well-known in the finance and economics literature and is often adopted by the relevant literature to locate countries vis-à-vis the LME and CME ideal categories (see, e.g., Boschma and Capone, 2015). Our PCA reveals four predominant models of capitalism, the LME and CME types, and two additional mixed models of capitalism, including those typically encountered in transitional or developing economies with some distinguishing CME or LME features.

Using several principal component regressions, we provide evidence that countries closer to the LME ideal type with financial market depth appear to have an advantage in generating green innovation. These countries are positively associated with all our measures of green innovation, and their coefficients are both statistically and economically significant. In line with the extant literature, it is mainly among those indicators with a greater short-term focus that these countries' coefficients show the greatest positive

[1] The Leaders' Summit on Climate took place in April 2021 and hosted the leaders of 40 countries representing more than half of global GDP and associated emissions (for more information, see the link). Also see https://www.climatewatchdata.org/net-zero-tracker for how net-zero targets are set at a country level.

magnitudes, while although positive, the indicators tracking their longer-term relative advantage and commitment to sustainable initiatives are substantially smaller. Interestingly, our analysis finds countries exhibiting a coordinated type of capitalism and mixed models are either negatively or not significantly associated with green technological developments. on To analyse the implication of those technologies, we employ the renewable energy mix to measure as proxy the application of green innovation. The results show that the characteristics underpinning LMEs load less heavily than those of more coordinated markets on innovation application. The coefficients of LMEs and mixed capitalism are indeed negative and significant in all our regression specifications. We have also performed several robustness tests, including changes in the principal component selection strategies, additional control variables and tests for other moderator and mediator variables. All tests leave our core findings unchanged.

Our work brings at least three contributions to the extant literature on institutions and green innovation. First, we contribute to the VOC literature by considering an extensive number of countries (53) over a long – twenty-one-year – time horizon and identifying the four models of capitalism that best represent them. We perform this task using a principal component analysis, a data-driven approach allowing us to locate the belonging of a country on the LME-CME spectrum, but without imposing any a priori restrictions on their allocation. This approach improves prior work of much of the early literature on VOC that took a dichotomous approach, arguing that most advanced economies fell either into the LME or CME camp and speaks to later work that instead has also sought to locate a much wider range of individual economies either on a continuum between these two poles and/or through introducing further categories (Herrmann & Peine, 2011; Witt & Jackson, 2016; Amable, 2003).

Second, we contribute to the literature on green innovation and green finance, inspecting the determinants and pre-conditions explaining countries' differences in the successful development of green patents. In particular, we show that macro- and micro-economic indicators of countries' institutions and knowledge-sharing systems, such as the financial system, matter and contribute to explaining the difference in countries' success in the development of green technologies. By pursuing these questions, we also contribute to a fast-developing body of work that explores VOC and social responsibility (Matten & Moon, 2008; 2020) and commitment to green innovation and green issues more generally (Gallego-Álvarez & Pucheta-Martínez, 2020; Surroca et al., 2020; Walker et al., 2019; Andreou & Kellard, 2021).

Finally, we advance the understanding of institutional effects on "true" *environmental sustainability*, a substantially more far-reaching concept than *green patenting*. We argue that if green innovation represents the creation of new technologies and forms of production to reduce environmental risks, it is only when the implementation of such innovations occurs that *true sustainability* can be achieved. Therefore, it is crucial to consider the development and application (implementation) of green innovation in tandem when assessing institutions' effects on *environmental sustainability*. However, the relevant drivers, measurements and applications remain underexplored in the extant literature. Our paper aims to address this gap and assess the application of such technology in relation to the institutional characteristics of the countries considered in our analysis.

The rest of the paper is structured as follows: Section 2 provides an overview of the literature, develops our theory related to green innovation, and subsequently outlines our testable hypotheses. Section 3 comprehensively describes our large and novel dataset and explains the proposed methodology. Section 4 presents and discusses the empirical analysis and reports additional robustness tests performed on our baseline regression models. Finally, Section 5 concludes.

2. Literature and hypotheses development

2.1. Comparative capitalism, financing and innovation

The literature on comparative capitalism highlights the relationship between national institutional configurations, firms and other socio-economic actors, and intra-organizational practice (Hall, 2015; Wood et al., 2014). This includes linking institutional context with types of innovation (Hall, 2015; c.f. Herrman and Peine, 2011). Such work argues that within LMEs (e.g., the developed Anglo-Saxon economies), radical product or service innovation was more likely given that relevant LME characteristics include financial market depth, shareholder protection, and strong generic educational systems. These characteristics, coupled with relatively high intra-firm mobility, diffuse knowledge across sectors (Herrmann and Peine, 2011; Thelen, 2012), leading to quicker, more radical innovation.

In contrast to LMEs, CMEs (e.g., the Rhineland economies, Scandinavia, and Japan) are more prone to incremental innovation (Herrmann & Peine, 2011; Hall, 2015) given high levels of mutual interdependence and less dominant financial markets, backed up by relatively high levels of security of tenure, that allow for the gradual development of organisational specific knowledge, building on the foundation of solid vocational and skills training. Of course, as noted earlier, other accounts propose that even the most advanced societies are not easily categorised into two camps. More data-driven approaches have highlighted the need to consider a wide range of institutional features in locating countries somewhere between the LME/CME poles (Witt & Jackson, 2016; Amable, 2003).

It is also important to note that the financial development literature also supports the idea that the type and level of innovation are related to financial systems, which are more prevalent in either LMEs or CMEs. The antecedents of such work can be traced back at least to Rajan and Zingales (1998), who note that financial development enhances growth, particularly within industries that are more dependent on external financing, by reducing the cost of capital. This mechanism operates via well-developed equity markets (i.e., in LMEs) by reducing the moral hazard and adverse selection issues associated with innovation external financing, with equity market prices providing useful information for investors and given there are no collateral requirements (Brown et al., 2009). By contrast, in bank-based financial systems (i.e., CMEs), the need for collateral (ibid.) and the absence of price signals (Beck and Levine, 2002) impede external financing of innovation. Hsu et al. (2014) show that these channels are even more important in the context of innovation in high technology industries as such firms are typically riskier than lower-technology alternatives, have less collateral available given their high level of intangible assets, and banks are typically keen to avoid such risky investment. Similar arguments apply to the extent that the characteristics of green innovation can be considered analogous to high technology.

In general terms, innovation is a complex phenomenon to measure, and patenting is an incomplete measure, even of radical innovative capabilities (Shu et al., 2015). Nonetheless, a body of work has highlighted a much greater propensity to patenting in LMEs, which might reflect a greater tendency to radical innovation (Taylor, 2004; Becker, 2009; Boschma & Capone, 2015). However, later work has depicted high levels of patenting as a mixed blessing in that it can serve as a barrier to incremental innovation; excessive patenting constrains leapfrogging (Jessop, 2011; Becker, 2009). In any case, this would still suggest some relationship between the capitalist archetype and innovative capabilities. Our study extends the literature by focusing on green innovation and activities that straddle intra- and extra-organizational variations in the usage of renewables. In internal terms, such use may make for more predictable input costs (Wood, 2016) and may be facilitated by informal and formal regulations around the need to advance sustainability (ibid.). In external terms, this will reflect the state and regulation of energy markets, national policies around renewables, and financial investor priorities, which, in turn, are closely bound up with national institutional traditions (Wood, 2016).

2.2. Green innovation and hypotheses development

We employ several measures for green innovation, most of them relying on environmental patents data. The use of patents *per se* is standard in the innovation literature (see Witt & Jackson, 2016; Taylor, 2004; Akkermans et al., 2009; Maskus, 2010; Stucki, 2019).[2] Like all other forms of innovation, environmentally sustainable innovation is potentially affected by the institutional coupling of innovative countries, by the mechanisms of knowledge creation and transmission (e.g., sharing), as well as by labour-employer relationships in firms and availability and type of financing. As noted above, LMEs are thought to present strong educational and research systems, high intra-firm mobility, and rapid knowledge diffusion across sectors (Thelen, 2012), and relatively deep financial markets to underpin investment in research and development. Such financial markets are typically populated with a greater variety of actor types, including venture capitalists and business angels. Hsu et al. (2014) also show that high-technology industries dependent on external finance are more innovative in countries with more developed equity markets. Overall, the above combination of factors creates a significant advantage for firms that want to develop green innovation patents (c.f. Hall and Soskice, 2001) and leads to our first hypothesis:

H1: *Economies closer to the liberal market end of the spectrum generate more environmentally sustainable innovations than coordinated market economies.*

Of course, producing environmentally related patents *per se* is not a measure of ‘true sustainability.’ It might be just ‘window dressing’ in practice, improving some key performance indicators around corporate social responsibility (CSR) with a view to reputation building or recovery (see Matten & Moon, 2008) but reflecting only minimal improvement of existing products. Moreover, firms may patent something not to operationalise it themselves but rather through either licensing or enclosing a domain to circumscribe competitors’ scope of innovation (Jessop, 2011). Additionally, even if a patent does result in a product, this product might commonly be purchased and applied overseas away from the domestic economy.

As noted earlier, the VOC approach has been used to explain variations in national proclivity to mitigate climate change around the world and, indeed, green decisions at the firm level (Gallego-Álvarez and Pucheta-Martínez, 2020; Surroca et al., 2020; Walker et al., 2019). Walker et al. (2019) conclude that greater firm responsibility is associated with better organisational performance outcomes in the case of CMEs and worse in LMEs; this might suggest that, in financial terms, CME firms have more incentives to apply green innovations (Wood et al., 2020). Doh et al. (2021) note that CMEs are more prone to make use of renewable energy sources, and the converse is true with LMEs, reflecting both long institutional traditions and the relative availability of capital for long versus short-term investments (cf. Allen et al., 2021).

Indeed, an extensive body of literature suggests that a significant gap in innovation systems in LMEs is that they are much better at coming up with new products than securing a competitive advantage in manufacturing due to innovation (Jessop, 2011). On the one hand, it has been argued that green technologies involve a fundamental paradigm shift, requiring a completely different approach to manufacturing, which may render previous shortfalls in innovation systems in this sphere less relevant, and, indeed, there have been several recent examples of apparent manufacturing success of green products in the US, most notably Tesla (Valentin, 2019). On the other hand, more critical accounts argue that the jury is still out on such matters, and Tesla has indeed faced a number of challenges in production that are not typically experienced by major car manufacturers in more coordinated economies (Teece, 2018). In short, the question emerges as to whether more liberal markets have been able to extend their advantages in many areas of innovation to encompass green technologies and whether this might serve as a basis for a revival in manufacturing competitiveness.

A further complicating factor is that polluting industries may be associated with the disproportionate usage of non-market strategies adopted to secure subsidies and erect barriers against the progress of emerging new technology-centred industries that threaten to render them irrelevant (Downie, 2017). Once they seriously start threatening (oil- and gas-centred) incumbents, new green technologies typically run into political headwinds (Stokes & Breetz, 2018). First past the post electoral systems are commonly encountered

[2] Of course, as with any other proxy, one needs to be careful to bear in mind any limitations when using patents as an indicator of innovation. For example, patent data may not always reflect innovation that is occurring outside the patenting system: either in countries without sufficient patenting laws or where there are other mechanisms to protect new technology (see Moser, 2013). As explained later in section 3.1.1, we also employ other dependent variables including relative advantage in environment-related technological development, or participation in programs like the UN Global Compact.

in LMEs, where elections are usually decided by small groups of ideologically uncommitted voters in swing constituencies, making them particularly conducive to firms pursuing non-market strategies (Goergen et al., 2009; Gourevitch & Shinn, 2010). Indeed, an emerging body of work highlights how oil and gas firms in the US and UK have successfully advanced their interests and impeded the development of green alternative energy industries through such strategies (Downie, 2017). Again, this would suggest that LMEs would be less effective in rolling out green technologies than in more coordinated markets.

To develop the argument further, consider that countries such as France, Germany and Sweden underpin a coordinated market system with multi-stakeholder types of governance (Ahlering & Deakin, 2007). Consequently, relatively long periods are tolerated for generating financial returns. On the other hand, in the established LMEs (e.g., the US and the UK), shareholders and financiers demand returns over relatively short horizons. Within the most advanced societies, these divisions correspond to the Liberal Market / Coordinated Market archetypes encountered in the VOC literature; however, many argue that many other features (such as national innovation systems) help distinguish these systems in addition to private property rights (Witt & Jackson, 2016; Hall, 2015). Assuming a typically sizeable upfront cost of applying green innovation, we can propose our second hypothesis:

H2: *Economies with a higher degree of coordination will be considerably more successful than more liberal ones in applying environmentally sustainable innovations and, hence, reducing their economic activity's environmental impact.*

Of course, if H1 and H2 both hold, they imply an uncomfortable corollary: factors that make liberal economies successful generators of green innovation, including easier access to finance, may relatively impede their more extensive application of green innovation via the demand for higher short-term returns. In other words, although it is widely predicted that they usher in a new production paradigm, it may be the case that green innovations follow the existing patterns of national innovation systems. With regard to the latter, LMEs will be much better at coming up with innovative new technologies than rolling them out (see Witt and Jackson, 2016). In contrast, CMEs, with their typically bank-based financial systems, will be better at the application of green technologies.

3. Data and methodology

3.1. Data collection and variables

To analyse green innovation and the extent to which such innovation depends on the hosting economy's type of capitalism, we build an extensive panel dataset of green innovation identifiers and institutional factors, including those related to the financial system. Specifically, we employ annual data for 53 countries – both OECD and others – from 2000 to 2020.[3] Section 3.1.1 describes our dependent variables, whilst Section 3.1.2 examines the institutional indicators.

3.1.1. Dependent variables

We employ several relevant dependent variables to test our hypotheses and address the different facets of green innovation. On the one hand, we select variables that capture the overall size of patents related to green innovation and, on the other hand, a dependent variable that captures the application of green innovations. Data for such variables are taken from the OECD Green Growth Indicators and the Policy Instruments for the Environment (PINE) database. This dataset contains extensive information on a firm's newly developed environment (green) patents, R&D expenditure, and government subsidies for more than 90 countries globally. All the patents considered in the OECD Green Growth database have a patent size of 2, reflecting just "claimed priority" applications based on the inventions' high value (in terms of expected impact and commercial value). The OECD sees Patent size 2 as a high-value technological patents given the high cost of patenting this type and the greater coverage of the patenting globally. In Figs. 1 and 2, we provide a graphical representation of the total amount of patents and the environment-friendly patents developed by each of our countries between 2000 and 2020.

In the Online Appendix A.1, we describe the chosen dependent variables. Our first measure for environmentally sustainable innovation is 'green_tech_perc', representing the share of domestic patents attached to environment-related technologies as a percentage of all patents registered by that country in a given year. This measure is taken from the OECD Green Growth indicators. Secondly, we use an index called "relative advantage in environment-related technologies" or 'rel_adv_env'. This index is also part of the OECD Green Growth indicators. It is computed as follows: "the ratio of 1) the share of environment-related inventions on all inventions (in all technologies) at home and 2) the share of environment-related inventions on all inventions (in all technologies) in the world" (Haščič & Migotto, 2015). Compared to other measures, this indicator does not represent an output measure of technology. Still, it assesses the importance of green development in the innovation mix of each country relative to the rest of the world. It represents a concept comparable to the Witt and Jackson (2016) definition of a country's comparative advantage in environmental innovation.

Thirdly, we use 'env_inv', representing the sum of environmental patents seeking protection in a given country over the last three years (T-3 to T) as a share of all environmental inventions that sought protection in the same period worldwide, whilst finally, we use a synthetic measure of countries commitment to green innovation via their registration in the UN Global Compact program (labelled

[3] We sourced institutional variables from Witt & Jackson (2016) and expanded their country coverage (from 22 OECD countries to 53 countries across the globe, both OECD and non-OECD) and time coverage. This has been achieved by combining data from Jackson (2005), Botero et al. (2004) and La Porta (2006) with other survey data from the Global Competitiveness Report, the ILO National Labour Law Profiles, Jelle Visser ICTWSS Database Version 5.1, ETUI data, and Thomson Reuters Practical Law database (see Online Appendix A.1).

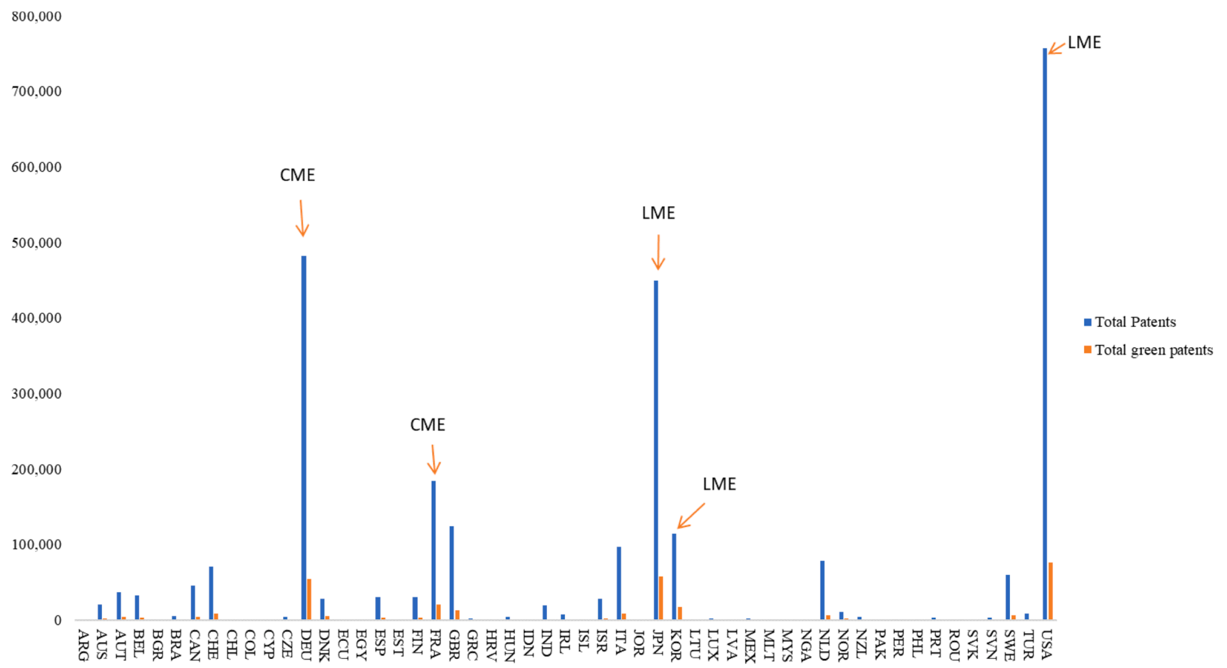

Fig. 1. Graphical comparison of individual countries' patent output (Category 2 or higher) Fig. 1 visually inspect the total patents developed by the countries in our sample over the 2000–2020 period. Note that we report in this graph only patent output in the patent category 2 or above, classified by the OECD as high-value technological patents. *Source.* OECD Statistics (Technology Development – number of patents).

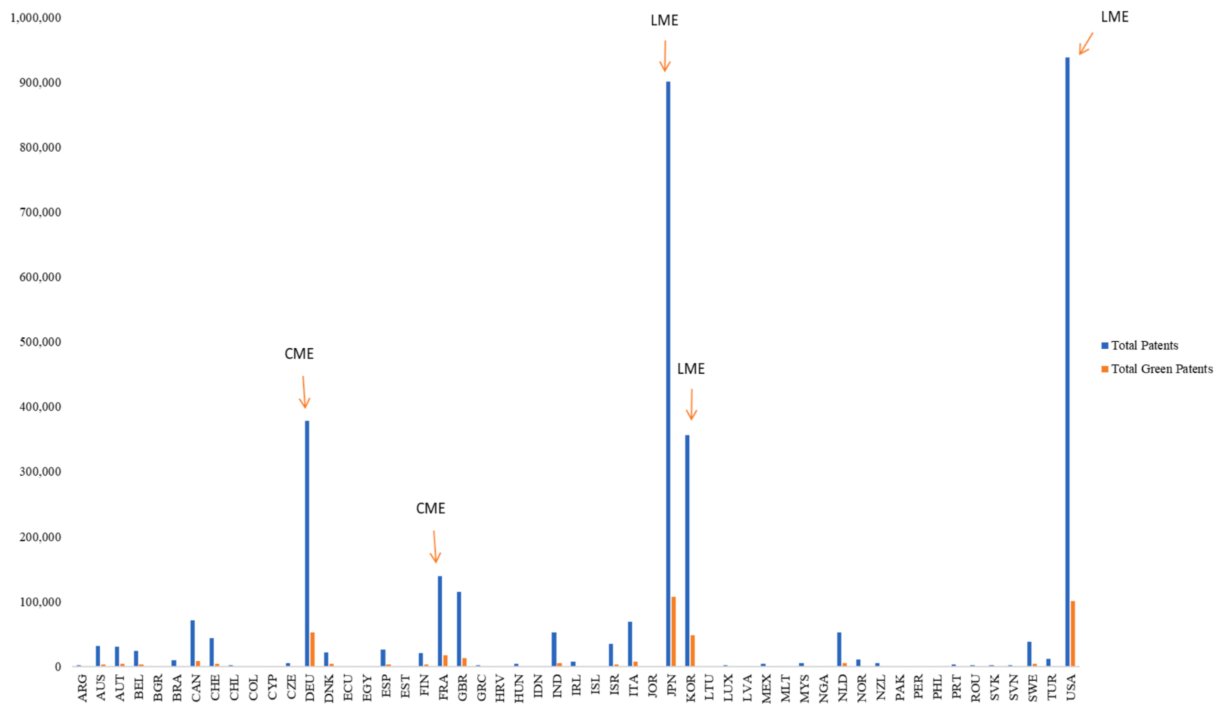

Fig. 2. Graphical comparison of individual countries' patent output (All Patent Categories) Fig. 2 shows the total patent output of the countries used in our sample over the 2000–2020 period. In the histogram, the blue bar corresponds to brown patents, and the orange one represents green patents instead. *Source.* OECD Statistics (Technology Development – number of patents). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

'subs_GC'). This program is a voluntary disclosure of involvement by participating companies (in a given country) in environmentally sustainable policies. After a firm subscribes to this program, companies are invited to participate in socially responsible initiatives and practices, such as the 'Anti-Corruption Working Group Initiative', 'Business for Peace Signatories Initiative', 'Call to Action: Anti-Corruption and the Post-2015′, 'Carbon Pricing Champions Initiative', 'Child Labour Platform Initiative', 'Human Rights and Labour Working Group Initiative' and many more. We computed the cumulated number of companies registering for the program in each year and country to build this indicator.

After considering output measures of green innovation, we examine the *application* of green innovation. To provide an appropriate proxy, aware of the limited data availability, we follow the extant literature and examine how innovative products are used and the processes that reduce greenhouse gas emissions. At an aggregate, country-level, the application of green innovation is perhaps most clearly seen in the 'Renewable Energy Mix', employed in work such as Allen et al. (2021). Indeed, one might argue that the renewable energy mix is the most crucial indicator of a country's application of green technology (see Doh et al., 2021). We measure the 'Renewable Energy Mix' by the share of renewable energy consumption in the country's total energy consumption.[4] Data for this variable are collected from the Sustainable Energy for All (SE4ALL) database, included in the SE4ALL Global Tracking Framework led jointly by the World Bank, the International Energy Agency, and the Energy Sector Management Assistance Program.

Finally, to further investigate the relation between innovation output and environmental impact as a dependent variable, we consider again patents (both green and total patents), which we scale by greenhouse gas emissions. The latter variable has been constructed by using country-level "total patent applications" each year (available from the OECD Patent Database) divided by Total Greenhouse emissions (retrieved from Emission Database for Global Atmospheric Research, EDGAR). Note that a detailed description of our dataset is also available in the Online Appendix A.1.

3.1.2. Institutional indicators

As per Hall and Soskice (2001), we defined five standard institutional domains: corporate governance, inter-firm relations, employment relations, firm hierarchy, and education and training, as measures of market primacy or coordination. Subsequently and following Witt and Jackson (2016), we use a wide range of variables to identify different characteristics of capitalism and locate individual economies relative to each other (see Online Appendix A.1). As explained in more detail in Section 3.2, all these indicators will be combined into different principal components to distinguish the appropriate capitalistic model identified by our sample of countries.

The corporate governance domain uses three variables: *shareholder protection*, *firm-required disclosure* and *financial market depth*. The primary assumption behind the construction of this domain is that in more liberalised markets, firms will rely more heavily on financial markets for accessing finance and as a coordinating mechanism, which will result in more transparent disclosure requirements and better shareholder protection (e.g., Li et al., 2017). Additionally, the larger number of investors in such economies will positively affect firms' capitalisation – especially that of big firms – and trading volume, enhancing the financial market depth of these economies.

Note that the higher (lower) the score of each corporate governance domain, the higher (lower) the likelihood that the analysed country has a more liberal (or coordinated) type of capitalism. Due to the lack of continuous data on shareholder protection and on countries' disclosure requirements or the lack of a Corporate Governance quality index that can be used for a global comparison of countries' corporate governance standards, the creation of this indicator required an extensive matching of publicly available datasets. Specifically, for most of the sample countries, we merged the La Porta et al. (2006) corporate governance variables ('*bdn_dire*' and '*disclose*') for the years ranging from 2000 to 2006, with survey data from the World Bank 'Ease of Doing Business' database for the remaining years. These data sources present an almost identical survey format and are both designed by Andrei Shleifer, a co-author of La Porta et al. (2006). For a few countries not covered in the World Bank Survey or La Porta et al. (2006), we use survey data collected by the World Economic Forum (WEF) in the Global Competitiveness Report.[5] Finally, we collected financial market depth data from the IMF Financial Development Statistics.

The inter-firm relations domain is built considering how prominent merger and acquisition (M&A) transactions are for domestic firms seeking access to innovative technologies. As M&A is a mechanism to acquire strategic control of a firm, we expect its use to be more prevalent in liberal economies because of the greater use of direct market transactions and lower transaction costs. For example, Georgieva et al. (2012), among others, find that US firms are more likely to form joint-ventures through cross-border M&As (i.e., full-scale M&As) for technology acquisition and transfer between joint venture partners. For the collection of M&A data, we use S&P Capital IQ whilst employing World Bank Statistics for relevant GDP data.

The employment relations domain is constructed around four variables: *Degree of wage coordination*, *short-term employment*, *employment protection* and *hiring and firing practices*. The idea behind the construction of this domain is that given the greater shareholder focus and laissez-faire approach (i.e., lower government intervention) of liberal governments, employee safeguards will be much looser for economies closer to the liberal market ideal. For this reason, a high value of each of these indicators – apart from *employment protection* – will be associated with more liberal markets, whilst vice versa, a low value is associated with more coordinated

[4] Note that our results are qualitatively similar if we instead consider the share of renewable energy supply in total energy supply employing data from the same provider. Of course, our approach doesn't trace a direct line between the patent data and their varied application in different countries. As far as we are aware, data doesn't exist to allow the construction of such a measure.

[5] The countries are Brazil, India, Indonesia, Japan, Nigeria, Pakistan, Philippines, and Switzerland.

ones.[6] To control for employment relations, we combined multiple datasets, such as survey data from the Global Competitiveness Report for the *degree of wage coordination* and *hiring and firing practices*, whilst we constructed *short-term employment* and *employment protection* variables using OECD Statistics.

The degree of firm hierarchy is identified using several dimensions: in particular, employees' participation in the management of the firm, the hierarchical structure of the firm and employee representation in the firm. Its identification is achieved using three variables: *Employee Board-level representation*, *Labour-employer relationship*, and *Works Council rights*. In this domain, as in all others, all country variables span from one category of capitalism to the other. In the case of *Board-level employee representation*, high employee representation in public or private firms (or both) is associated with a highly coordinated economy, presenting proactive labour regulation. From a firm perspective, the same can be said about a high value in the *Labour-employer index*, implying a cooperative relationship between management and employees and indicative of a more bottom-up management approach. Finally, for the *Works Council rights* indicator, high values are associated with high government intervention and coordination of the job market, whilst low scores, with a more liberal approach. For *employee Board-level representation*, we used the Jackson (2005) and Witt and Jackson (2016) six-dimensional index on employee representation and computed the values for the remaining countries using countries' Corporate Governance Codes supplemented by secondary data collected by the OECD Corporate Governance Survey, European Trade Union Institute (ETUI) data, OECD (2014) and Thomson Reuters Practical Law database. Labour-Employer relationship data has been obtained from the Global Competitiveness Report survey data. Finally, Work Council rights data has been gathered from Jelle Visser ICTWSS Database Version 5.1, ETUI data and authors' calculations based on country Labour Law.[7]

Following Witt and Jackson (2016), we proxy the education and training dimension using the proportion of students choosing upper-secondary education and the proportion of students choosing university education. We subsequently assume that coordinated market economies will present high scores in the former and lower in the latter, whilst an opposite pattern will represent liberal market economies. All data related to these variables has been collected from OECD Education Statistics. In the Online Appendix A.2, we provide some relevant summary statistics.

3.2. Methodology

3.2.1. Synthetic models of capitalism

In order to deal with the challenges of modelling capitalistic regimes, and as described above, we collect a wide range of indicators, including a number of financial measures, following the VOC literature. We employ principal component analysis (PCA) to group the countries according to more coordinated, liberal, or mixed models of capitalism – a similar methodological approach to both Hall and Soskice (2001) and Witt and Jackson (2016).

PCA is a data reduction method appropriate to express multivariate regression models using fewer dimensions and minimal information loss (Abdi and Williams, 2010). It works by exploiting the correlation in the dataset variables to create new synthetic uncorrelated variables. This methodology, along with other data reduction techniques (e.g., factor analysis), is used across disciplines and is well-known in the finance and management literature (Jolliffe & Cadima, 2016; Abdi and Williams, 2010; Görtler et al., 2019; Bouveyron et al., 2020). The main advantage of the PCA over other methodologies is that it drastically decreases the dataset dimensions in an interpretable way while minimising information loss (Jolliffe & Cadima, 2016).

The PCA procedure comprises three main steps: (i) perform the PCA on the explanatory variable data matrix, and once obtained, the principal components preserve those explaining the highest amount of variability; (ii) compute the factor loadings of the previously selected principal components, representing the correlation between the original explanatory variables and the principal components (or the proportion of variance of each explanatory variable accounted for by the considered principal component); and (iii) use the newly created components loadings to construct the final principal component regression (PCR) estimator to regress against the dependent variable of the model. Additionally, considering the different scales of the variables we adopted, we also scale the analysed variables to ensure their comparability (Abdi and Williams, 2010; Jolliffe, 2011).[8]

As with other statistical methods, there are, of course, limitations in using PCA, including that "it may be difficult or dangerous to try to read too much 'meaning' into the components" (Chatfield and Collins, 2000:79). This restricts the interpretation of the principal components' coefficients in all our regressions to a discussion about sign and relative size. Still, since all the original input variables are a linear combination of the newly created ones, the interpretability of PCA results is substantially more straightforward than those of non-linear data reduction models. In line with the literature, we choose the number of principal components based on whether their eigenvalues are higher than 1. This ensures they explain more variation than the original regressors, as the Kaiser method suggests (see Kaiser, 1961). In Table 1 we report the eigenvalues of the considered principal components.

Apart from the most important advantage of using PCA, which in our case is creating "synthetic" capitalism variables, there are a few more interesting benefits to adopting this methodology. In particular, the resolution of potential multicollinearity problems, which, given the nature of our data and the many of the selected regressors, may arise. For instance, it is easy to argue that shareholder protection is highly correlated with employee representation, as the higher diversity of the Board members can reduce agency

[6] A more detailed description of the variables is reported in Online Appendix A.1.

[7] These have been cross-checked using Thomson Reuters Practical Law database, USA International Business Publications (2014), and the ILO National Labour Law Profiles database.

[8] Given the different scales of the independent variables (see summary statistics in Online Appendix A.2), we normalise the observations for each variable using the formula: $[x_i - \text{mean}(x)]/\text{std}(x)$.

Table 1
Eigenvalues and cumulative variance explained. In Table 1, we show the eigenvalues of all synthetic variables (principal components) considered in our study and the respective total variance which they explain.

Princ. Comp.	*Eigenvalue*	*Variance (%)*	*Cumulative Variance (%)*
Dim.1 (CME)	**2.9282989**	**20.91642**	**20.91642**
Dim.2 (LME)	**2.4353794**	**17.395567**	**38.31199**
Dim.3 (CDE)	**1.6884204**	**12.060146**	**50.37213**
Dim.4 (ALME)	**1.0169232**	**7.263737**	**57.63587**
Dim.5	0.933241	6.666007	64.30188
Dim.6	0.8321642	5.94403	70.24591
Dim.7	0.7720473	5.514624	75.76053
Dim.8	0.7575644	5.411175	81.1717
Dim.9	0.5935752	4.239823	85.41153
Dim.10	0.5506013	3.932867	89.34439
Dim.11	0.4505423	3.218159	92.56255
Dim.12	0.4255376	3.039554	95.60211
Dim.13	0.3522586	2.516133	98.11824
Dim.14	0.2634463	1.881759	100

Notes: Highlighted are the selected principal components, i.e., those with Eigenvalue > 1 (see Kaiser, 1961).

problems (Jensen and Meckling, 1976). Using PCA, multicollinearity problems are easily solved as once principal components are created, they are orthogonal to each other by construction. Furthermore, given those components explaining the highest variability are selected, this methodology enables us to substantially reduce the number of parameters used in the regression, making the model more parsimonious.

Our data collection required extensive matching of available datasets, coming both from publicly available sources, such as the OECD, ILO, ETUI and World Bank, and relevant papers, such as Jackson (2005), Botero et al. (2004) and La Porta et al. (2006). As such, some variables contain missing observations, such as 'tenure_m_12′, 'empl_protect_dism', 'occ_train', and 'uni_train'. To account for this, we perform our analysis using Josse et al. (2012) regularised iterative PCA (coded in the R-package 'missMDA'). The methodology has been specifically built to perform PCA on data with missing observations. Other commonly used methods to deal with missing data (caused by a few variables) imply substituting the missing observations with the mean of the observations of the considered variable – a default option of many software packages when performing a PCA. As argued by Josse et al. (2012), this latter approach can provide satisfactory results in case of no multicollinearity; however, it suffers significant bias otherwise. The Josse et al. (2012) interpolation technique, using a simple iterative process, can predict missing values and considers both the similarity of individuals across all the variables and the links between all the analysed variables, essentially considering the structure in the data.

3.2.2. Results of the PCA

After we performed the PCA and selected the first four principal components (using Kaiser's criterion), we computed the factor loadings, representing the correlation between the initial explanatory variables and the principal components.[9] These loadings are essential when performing a PCA, as they represent the relationship between each variable and the principal component. In other words, when the loading is positive, the principal component comoves with the variable, representing a 'state' where this specific condition is present, whilst the opposite can be deduced when the loading is negative.

Using this framework, in Table 2, we can analyse the different capitalistic models identified by the four principal components under consideration. In Figures III and IV in Online Appendix A.3, we also provide a graphical representation of the correlation patterns of our original institutional variables in the principal component space. Also, in Figures V and VI in Online Appendix A.4, we plot the time variation of our first and second principal components to analyse more closely the institutional changes arising in the top-10 innovating countries included in our sample (based on their patent development).

Focusing on the first principal component (Dim.1) and its factor loadings, we can argue that it primarily represents a coordinated type of capitalism (employee-oriented), with a few features of economies closer to the liberal market ideal. Strikingly, it appears strongly positively correlated to variables such as works council rights 'wc_rights' and 'empl_prot', representing employment-related policies, and negatively correlated with most shareholder-friendly variables. It is also positively correlated with 'perc_M&A_asset', representing the proportion of M&A transactions that do not involve a change in the control of the target company. This component presents a few liberal characteristics given its positive factor loadings with respect to variables such as financial market depth 'fm_depth' and university training 'uni_train', but generally speaking, is negatively correlated with all core variables identifying liberal market economies (Dim.2 explained next). Therefore, from now on, we refer to Dim.1 as "CMEs".

Moving to the second principal component (Dim.2) in Table 2, this seems to capture a very liberal type of capitalism. Notably, the highest loadings attach to variables typical of LMEs, including the use of M&As 'M&A GDP', shareholder protections 'sharehold prot', flexible wages 'flex wage' or hiring and firing practices 'flex fire_hire', short job-tenure across industries 'tenure m 12′ and so on. Additionally, Dim.2 presents low scores on employment protection 'empl protect dism' and employees' representation 'empl rep' on corporate boards. As a result, we denominate Dim.2 as "LMEs".

[9] The sum of all squared loadings for a given variable is equal to 1.

Table 2
PCA factor loadings Table 2 shows the factor loadings of the first four principal components presented in Table 1 (which we selected based on the Kaiser method). In other words, we display the correlation between our original independent variables (which we used to build the principal components) and each of the newly created synthetic variables. Further in-depth information on the variables included in this Table is reported in Appendix A.1.

	Dim.1 (CMEs)	*Dim.2 (LMEs)*	*Dim.3 (CDEs)*	*Dim.4 (ALMEs)*
Shareholder Prot.	−0.07	0.48	−0.20	0.27
Required Discl.	−0.14	0.48	−0.29	−0.09
Fin. Mkt Depth	0.48	0.47	−0.06	−0.01
M&A Vol-to-GDP	−0.03	0.02	0.02	0.96
%Asset M&A/Tot. M&A	0.51	0.20	0.36	−0.01
Wage Flexibility	−0.58	0.40	0.29	0.07
%Short-term employed	−0.19	0.43	−0.55	0.01
Empl. Prot. Policies	0.25	−0.66	0.15	−0.09
Flexib. In Hire & Fire	−0.26	0.60	0.50	0.01
Employees Represent.	0.66	−0.17	0.21	0.01
Coop. Employer-Employee	0.32	0.48	0.59	0.06
Work Council Rights	0.84	−0.12	0.13	0.02
%Occupational Train.	0.66	0.43	−0.30	0.03
%Univ. Train.	0.53	0.35	−0.51	0.03

Analysing the last two principal components (Dim.3 and Dim.4), they correspond to the so-called "mixed models" of capitalism (see Witt and Jackson, 2016) in light of their lower degree of institutional convergence. In particular, Dim.3 represents countries with low levels of education (see 'uni train' and 'occ train') and, thus, potentially, low-income (or developing) economies with a considerable degree of state coordination. Furthermore, these economies are characterised by low financial market depth 'fm depth', shareholder protection 'sharehold prot', required disclosures 'req discl', and M&A activities 'M&A GDP', all highlighting low financial market development and low shareholder focus. Such countries also show strong coordination characteristics, and therefore, the principal component displays high scores on labour relations 'coop lab_emp' and employee-protection 'empl protect dism'. Hence, in the following sections, we call Dim.3 "Coordinated Developing Economies" or "CDEs".

Finally, Dim.4, analogously to Dim.3, presents low 'Education and Training' scores regarding occupational 'occ train' and tertiary training 'uni train'. However, the capitalistic style of this component is different from the previous dimension, being predominantly liberal. This can be gleaned from the more positive scores obtained on variables such as: shareholder protection 'sharehold prot', required disclosures 'req discl', M&A activity 'M&A GDP', financial market depth 'fm depth' and 'flex_wage' variables. However, it could also be argued that labour regulation in these economies appears slightly more restrictive for employers than in "pure LMEs", given the positive score (although small) on labour protection from workers' unions in case of dismissals 'wc_rights'. Therefore, we name this principal component "Ambiguous Liberal Market Economies" or "ALMEs".

3.3. Descriptive statistics

3.3.1. National institutional settings

Table 3, presents country-specific average scores assumed by each principal component over our sample period. In particular, this aids in detecting the prevalent institutional regime within each national context and how close they veer towards the LME or CME ideals according to the features encompassed in our analysis. Ultimately, following Hall and Soskice (2001), we allocate each country as closer to one or other of their two archetypes of capitalism.

In Panel A, we present 14 countries characterised by predominant coordination characteristics. These are typically characterised by high average scores on the CMEs principal component and low (or negative) scores with respect to LMEs. In the top section of Panel A, we position countries positively associated with CMEs and negatively associated with LMEs. At the bottom of Panel A, we present countries with a high and positive CMEs average score and a positive but much lower score concerning the LMEs principal component. We argue that the first group of countries (in the top section) have a higher degree of institutional convergence than the second group of countries (in the bottom section), which, despite being CMEs, still present some characteristics of LMEs. Some examples of CMEs with relatively high scores on the LME principal component are Nordic EU countries such as Sweden, Norway, and Finland, which, despite displaying a high level of state welfare and coordination, present relatively developed financial markets and corporate governance practices.

Panel B of Table 3 comprises 17 countries with a more liberal capitalistic approach. These countries display a high score on our second principal component (LMEs) and a low, primarily negative, score with CMEs. Indeed, with the exception of Australia, Ireland and Denmark, displaying a relatively strong degree of state coordination. Amongst these others, we find countries like the United States, Canada, United Kingdom and New Zealand, which constitute prominent examples of liberal market economies. Finally, in Panels C and D of Table 3, mixed models of capitalism are presented. In many cases, countries are characterised by a negative score on both CMEs and LMEs principal components and a positive association with one of the other two mixed models derived from our data-driven identification. Countries in Panel C have features that are typical of developing economies with a significant degree of state coordination, including those from Eastern Europe, South Asia, South America, and the Middle East. Countries displayed in Panel D present relatively more liberal features.

Table 3
National models of capitalism In Table 3, we present a detailed characterisation of the institutional settings of all countries included in our sample. In columns 2 to 5, we disclose the average principal component scores associated with each country in the analysis period (2000 to 2020). In column 6, we show whether we observe institutional convergence based on the average sign of the component scores or whether a particular country has characteristics common to multiple models of capitalism. In columns 7 and 8, we disclose the capitalistic model to which each country has been allocated by our empirical model based on its principal component score. In Panel A, we analyse Coordinated Market Economies (CMEs); in Panel B, Liberal Market Economies (LMEs); eventually, in Panels C and D, Mixed Models of Capitalism, such as Coordinated Developing Economies (CDEs) and Ambiguous Liberal Market Economies (ALMEs).

Panel A. Coordinated Market Economies (CMEs)

Country	Avg CMEs	Avg LMEs	Avg CDEs	Avg A-LMEs	Institutional Convergence	Classification	Full Classification
Belgium	2.31	−0.19	−0.44	−0.26	Yes	CME	CME
Italy	1.40	−1.82	−0.79	−0.18	Yes	CME	CME
Netherlands	3.45	−0.32	1.09	−0.11	Yes	CME	CME
Portugal	0.71	−1.44	−0.12	−0.24	Yes	CME	CME
Slovenia	1.51	−1.45	−0.31	−0.12	Yes	CME	CME
Austria	2.85	−1.11	0.68	0.06	No	CME	CME
Finland	2.95	0.77	−0.85	0.05	No	CME	CME
France	1.60	−0.69	−0.74	0.04	No	CME	CME
Germany	3.02	−1.39	0.34	0.11	No	CME	CME
Greece	1.08	−1.63	−1.00	0.18	No	CME	CME
Norway	2.72	0.14	−0.14	0.14	No	CME	CME
Spain	1.40	0.33	−1.05	−0.15	No	CME	CME
Sweden	3.73	0.18	−0.24	0.19	No	CME	CME

Panel B. Liberal Market Economies (LMEs)

Country	Avg CMEs	Avg LMEs	Avg CDEs	Avg A-LMEs	Institutional Convergence	Classification	Full Classification
Canada	−0.49	2.98	−0.12	−0.25	Yes	LME	LME
Korea	−0.90	0.67	−3.42	−0.19	Yes	LME	LME
Lithuania	−0.73	0.07	−0.35	0.05	Yes	LME	LME
New Zealand	−0.60	2.71	−0.79	−0.04	Yes	LME	LME
United States	−1.23	3.84	−0.19	0.05	Yes	LME	LME
Australia	1.03	1.67	−2.18	0.26	No	LME	LME
Cyprus	−0.64	0.40	0.03	0.07	No	LME	LME
Denmark	2.08	2.14	1.04	−0.01	No	LME	LME
Estonia	−0.85	1.09	0.45	0.21	No	LME	LME
Iceland	0.20	2.24	0.35	−0.03	No	LME	LME
Ireland	0.62	1.40	−0.25	−0.07	No	LME	LME
Israel	−0.54	1.13	0.22	−0.26	No	LME	LME
Japan	−0.16	1.57	0.16	−0.06	No	LME	LME
Latvia	−0.78	0.12	0.03	0.07	No	LME	LME
United Kingdom	0.09	2.73	0.58	−0.07	No	LME	LME

Panel C. Mixed Model of Capitalism (Coordinated Developing Economies, CDEs)

Country	Avg CMEs	Avg LMEs	Avg CDEs	Avg A-LMEs	Institutional Convergence	Classification	Full Classification
Croatia	−0.03	−1.38	0.36	−0.08	Yes	Mixed	CDEs
Czech Republic	0.54	−1.26	1.54	−0.07	Yes	Mixed	CDEs
India	−1.43	−0.88	0.68	−0.44	Yes	Mixed	CDEs
Indonesia	−1.81	−1.12	0.79	−0.51	Yes	Mixed	CDEs
Nigeria	−2.82	−1.24	1.13	−0.26	Yes	Mixed	CDEs
Pakistan	−1.58	−1.62	0.06	−0.40	Yes	Mixed	CDEs
Philippines	−1.58	−0.68	0.52	−0.29	Yes	Mixed	CDEs
Romania	−1.23	−0.69	0.68	−0.16	Yes	Mixed	CDEs
Slovak Republic	0.10	−1.46	1.43	−0.06	Yes	Mixed	CDEs
Egypt	−1.37	−1.85	0.34	0.03	No	Mixed	CDEs
Hungary	0.50	−0.55	1.16	0.07	No	Mixed	CDEs
Jordan	−1.94	−0.59	0.62	0.11	No	Mixed	CDEs
Luxembourg	1.33	−0.27	1.88	0.05	No	Mixed	CDEs
Malaysia	−1.46	1.17	1.51	−0.41	No	Mixed	CDEs

Panel D. Mixed Model of Capitalism (Ambiguous Liberal Market Economies, ALMEs)

Country	Avg CMEs	Avg LMEs	Avg CDEs	Avg A-LMEs	Institutional Convergence	Classification	Full Classification
Argentina	−0.37	−1.57	−2.05	0.13	Yes	Mixed	ALME
Brazil	−0.44	−0.22	−0.78	0.16	Yes	Mixed	ALME
Bulgaria	−1.17	−0.09	−0.12	0.02	Yes	Mixed	ALME
Chile	−1.35	0.77	−1.03	1.63	Yes	Mixed	ALME
Colombia	−1.86	0.16	−1.22	0.29	Yes	Mixed	ALME
Ecuador	−1.70	−1.92	−0.58	0.30	Yes	Mixed	ALME
Mexico	−2.15	−0.95	−0.43	0.02	Yes	Mixed	ALME

3.3.2. National institutional settings and green innovation output

After identifying national institutional settings, we provide descriptive statistics for each of our dependent variables of innovation output across the identified institutional regimes.

As evident from Table 4, importantly, LMEs appear to outperform CMEs and mixed models of capitalism with respect to all measures of innovation output. An exception to this appears to be the normalised variable capturing the number of companies' subscriptions to the UN Global Compact, whereby CMEs emerge as having a greater average subscription ra.

3.4. Panel regressions

After normalising our dependent variables to have a comparable scale with our normalised principal components, we estimate a fixed-effect regression model of the following form.[10]

$$Green_{i,t} = \alpha_i + \alpha_t + \beta_1 CMEs_{i,t} + \beta_2 LMEs_{i,t} + \beta_3 CDEs_{i,t} + \beta_4 ALMEs_{i,t} + \varepsilon_{i,t} \tag{1}$$

In (1), $Green_{i,t}$ corresponds to our dependent variables for a given country (i) and year (t) and 'CMEs', 'LMEs', 'CDEs', and 'ALMEs' represent the previously calculated principal components loadings, computed for each country and year. $\varepsilon_{i,t}$ denotes the iid error term and α_i ($i = 1,..,n$) represents a country-specific intercept, or fixed effect, capturing individual countries' time-invariant unobserved heterogeneities. We also include time fixed-effects in this regression specification, identified by the variable α_t. We use heteroscedasticity- and autocorrelation-consistent standard errors clustered at the country level in all our regressions. This approach allows us to test Hypothesis 1 (H1) in Section 2.3; in particular, if the hypothesis holds, we would expect positive and significant estimates of β_2 and negative and/or insignificant estimates of β_1.

Moving on to the assessment of Hypothesis 2 (H2), we examine the *adoption* of environment-friendly innovation by different capitalist economies. To perform this analysis, we collect data on renewable energy consumption (as a percentage of total final energy consumption) – also called "*Renewable_energymix*" – and regress against our previously adopted principal components. Equation (2), also estimated using a fixed-effects regression, reads therefore:

$$Renewableenergymix_{i,t} = \alpha_i + \alpha_t + \beta_1 CMEs_{i,t} + \beta_2 LMEs_{i,t} + \beta_3 CDEs_{i,t} + \beta_4 ALMEs_{i,t} + \varepsilon_{i,t} \tag{2}$$

This time, if H2 holds, we would expect positive and significant estimates of β_1 and negative and/or insignifcant estimates of β_2.

Finally, for further evidence and considering both innovation output and environmental impact, we estimate panel fixed-effects regressions using "Total Patents" or "Green Patents" scaled by greenhouse gas emissions as a dependent variable. Equation (3) is formulated as follows:

$$PatentsToEmissions_{i,t} = \alpha_i + \alpha_t + \beta_1\, CMEs_{i,t} + \beta_2\, LMEs_{i,t} + \beta_3\, CDEs_{i,t} + \beta_4\, ALMEs_{i,t} + \varepsilon_{i,t} \tag{3}$$

4. Empirical analysis

4.1. Green innovation output

Table 5 reports the results of the estimation of (1). Each column has the same set of explanatory variables and differs only in the dependent variable or its employment of fixed-effects.

Notably, the coefficient on the LMEs' principal component is typically positively and significantly associated with all our measures of output of green innovation ('green_tech_perc', 'rel_adv_env' and 'env_inv' of Table 5, respectively). This is consistent with our H1, whereby LMEs generate more environmentally green innovations than CMEs. In this vein, it is unsurprising to commonly observe the negative and/or insignificant coefficients with respect to CMEs, CDEs and ALMEs principal components, which is also consistent with H1.[11][12]

Bearing in mind the "high value" green innovation employed in our regressions (i.e., patented technologies with a patent family size of 2), these findings support and extend previous literature on VOC, suggesting that more liberal markets are more fertile environments for radical innovation (Hall and Soskice, 2001). The market-driven mechanisms characterising LMEs, as well as their top-down and shareholder-oriented culture and flexible use of the labour market, make these economies ideal for radical innovation, requiring "substantial shifts in product lines [for] the development of entirely new goods" (Hall and Soskice, 2001: 38). For this reason, we suggest that "high impact" green innovations find a suitable ecosystem in the most advanced LMEs, and, potentially, emerging

[10] In order to understand whether our model is better represented by a fixed or random effects model, we perform a Hausman test (see Hausman, 1978).

[11] Employing time fixed-effects, in addition to country fixed-effects, produces more modest evidence for positive and significant coefficients. This is perhaps unsurprising as the inclusion of time fixed-effects likely captures the persistence of innovation output and for this reason related studies tend to omit such effects. However, even with this approach, the overall conclusion remains the same: economies closer to the liberal end of the spectrum generate more green innovation than coordinated market alternatives.

[12] An exception to the negative and/or insignificant coefficients for the CME principal component can be found in Column (Akkermans et al., 2009) of Table 5, where the dependent variable is '*env_inv*'. It should be noted that the higher point values for the coefficients attached to the LME principal component still indicate an advantage for liberal markets.

Table 4
Innovation explained by our models of capitalism In Table 4, we present the average green innovation score associated with each model of capitalism (e.g., the average percentage of green patents-over-total patents developed by LMEs is 9.99). Further in-depth information on the variables included in this Table is reported in Appendix A.1.

Capitalistic model	Green Patents (%)	Relative Advantage in Green Tech	Green Technologies (%)	UN Global Compact
CME	10.38	1.03	17.29	**64.96**
LME	**10.80**	**1.07**	**19.26**	28.18
Mixed	10.71	1.06	3.46	27.66

Table 5
Explaining green innovation – Estimation of (1) Table 5 displays the results of our baseline principal component regression of the percentage of green patents in the mix (columns 1–2), the relative advantage in green technologies (columns 3–4), the percentage of green technologies (columns 5–6), the number of firms involved in the UN Global Compact (columns 7–8), on our institutional principal components. All regressions contain either country fixed-effects or country fixed-effects and time-fixed effects. Further in-depth information on the variables included in this Table is reported in Appendix A.1.

	(1) *green_tech_perc*		(2) *rel_adv_env*		(3) *env_inv*		(4) *subs_GC*	
Dim1 (CME)	−0.079	−0.137***	−0.111**	−0.134**	0.150***	0.127***	−0.045	−0.003
	(0.051)	(0.046)	(0.051)	(0.054)	(0.050)	(0.045)	(0.051)	(0.021)
Dim2 (LME)	0.175***	0.019	0.113***	0.075*	0.261***	0.150***	0.102**	0.008
	(0.043)	(0.042)	(0.044)	(0.042)	(0.043)	(0.041)	(0.044)	(0.019)
Dim3 (CDE)	−0.050	0.06	0.062	0.060	−0.166***	−0.067**	−0.146***	0.032
	(0.039)	(0.034)	(0.039)	(0.040)	(0.038)	(0.034)	(0.039)	(0.016)
Dim4(ALME)	−0.014	−0.013	−0.000	−0.000	−0.007	−0.006	−0.012	0.002
	(0.031)	(0.027)	(0.031)	(0.031)	(0.031)	(0.027)	(0.031)	(0.012)
Constant	−0.000	−0.773***	0.000	−0.038	−0.000	−0.746***	0.000	−0.945***
	(0.030)	(0.118)	(0.030)	(0.138)	(0.029)	(0.117)	(0.030)	(0.055)
Observations	1,113	1,113	1,113	1,113	1,113	1,113	1,113	1,113
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.020	0.297	0.017	0.05	0.055	0.310	0.018	0.849

Notes: Robust Ses are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% level.

markets closest to this end of the spectrum, especially given there is a contemporary global demand for eco-friendly products underpinned by increasing environmental awareness. Finally, in Table 5, our fourth dependent variable (*subs_GC*') and associated regressions examine the ability of different capitalisms to attract companies generating green innovation (among other sustainable outcomes). Allowing only for country fixed-effects, we find the LMEs dimension is positively and significantly associated with the number of companies involved in the UN Global Compact. By contrast, CMEs, CDEs and ALMEs are either negatively associated or insignificant. Adding time fixed-effects removes the empirical differences between the principal components. Given that '*subs_GC*', unlike our other three dependent variables in Table 5, is not a measure of green innovation output but a voluntary disclosure of environmentally committed firms, this equivocation is perhaps to be expected.

Overall, from the results presented in Table 6 we can conclude that countries closest to the LME type outperform others closer to the CME type in producing green technology, supporting H1. Moreover, in line with previous studies on patents at large (see Taylor, 2004; Akkermans et al., 2009; Boschma and Capone, 2015), our paper suggests that institutional convergence provides a better outcome in terms of development of green innovation. This is evidenced by the negative or insignificant coefficients of "mixed" capitalism models in many of the regressions (see Table 5) and appears particularly true for more coordinated mixed models of capitalism that are negative and significant predictors of green innovation.

4.2. *Utilisation of green innovation*

We now examine whether the application of environment-friendly innovation is lower in more liberal relative to more coordinated economies. Hence, we test whether our H2 holds. To do so, in Table 6, we report the estimation results of regression (2).

We observe that the coefficient for LMEs has a negative sign. This implies that, despite being more prolific in environmental patent development, as demonstrated in Table 5, LMEs are considerably less effective in their adoption. Specifically, when we consider countries' percentage of renewable energy consumption in their energy mix, we find that LMEs are negatively and significantly correlated with renewable energy consumption in columns (Abdi and Williams, 2010) and (Ahlering and Deakin, 2007). By contrast, countries with greater state coordination (i.e., CMEs and CDEs) appear positively associated with renewable energy consumption in both regressions. It would appear there is evidence to support H2. For ALMEs, we consistently find a positive and weakly significant association with renewable energy consumption.

Overall, this suggests a negative association between market liberalism and the application of green innovation, whilst a positive association exists in more coordinated economies. Moreover, it shows that countries with a mixed model of capitalism perform relatively well in the adoption of green technology (particularly CDEs) compared to the more institutional convergent types, indicating

Table 6

Explaining adoption of renewable energy – Estimation of (2). Table 6 displays the results of our second baseline principal component regression of the percentage of renewable energy in the country's energy mix (columns 1 and 2) on our institutional principal components. All regressions are supplemented with country fixed-effects in column 1 and column 2 with year (time) fixed-effects. Further in-depth information on the variables included in this Table is reported in Appendix A.1.

	(1) *Renewable energy mix*	(2) *Renewable energy mix*
Dim1 (CME)	0.072**	0.063**
	(0.031)	(0.031)
Dim2 (LME)	−0.101**	−0.124**
	(0.047)	(0.048)
Dim3 (CDE)	0.267***	0.291***
	(0.040)	(0.042)
Dim4 (ALME)	0.128*	0.136*
	(0.078)	(0.075)
Constant	−9.095***	−9.359***
	(0.059)	(0.291)
Observations	1,058	1,058
Country FE	Yes	Yes
Time FE	No	Yes
R-squared	0.047	0.066

Notes: Robust Ses are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% level.

these countries' commitment to a sustainable future.

4.3. Green innovation vs greenhouse emissions

To further investigate the results of Sections 4.1 and 4.2, we combine innovation output and environmental impact in our dependent variable. In particular, we consider again patents, both green patents and total patents, which we scale by greenhouse emissions. This will provide insight into whether environmental innovation is still higher in LMEs, even after considering any greater environmental impact.

Table 7 provides further evidence for LME green innovation productivity since LMEs are positively associated with both types of innovations even after accounting for their environmental impact. Specifically, we find the coefficient of the principal component identifying LMEs is equal to approximately 0.47 in the first column ('Total patents/Greenhouse emissions') and 0.25 in the third column ('Green patents/Greenhouse emissions'). With respect to CMEs, and again focusing on columns 1 and 3, we find these economies are not significantly associated with innovation output. This provides evidence of a similar signed association with innovation output across different types of innovation. Lastly, consistent with our earlier baseline results, CDEs and ALMEs appear negatively or not significantly related to innovation output.

We observe similar results when including time fixed-effects (see columns 2 and 4 of Table 7). LMEs are positively associated with innovation output; conversely, CMEs have a negative and significant effect on total patent-to-greenhouse emissions and an insignificant effect on green patent output. With respect to mixed models of capitalism, similar to our results without time fixed-effects, we

Table 7

Explaining patents to emissions – Estimation of (3). Table 7 displays the results of our third baseline principal component regression of the ratio of total (all) patents-to-greenhouse emissions (columns 1–2) and green patents-to-greenhouse emissions (in columns 3–4) on our institutional principal components. All regressions contain either country fixed-effects or country fixed-effects and time-fixed effects. Further in-depth information on the variables included in this Table is reported in Appendix A.1.

	(1) *Total patents/Greenhouse emission*		(2) *Green patents/Greenhouse emission*	
Dim1 (CME)	0.059	−0.102**	0.061	−0.012
	(0.048)	(0.044)	(0.051)	(0.042)
Dim2 (LME)	0.474***	0.185***	0.245***	0.066*
	(0.041)	(0.041)	(0.043)	(0.038)
Dim3 (CDE)	−0.269***	−0.158***	−0.176***	−0.048
	(0.036)	(0.033)	(0.038)	(0.031)
Dim4 (ALME)	0.020	−0.001	0.026	0.021
	(0.029)	(0.026)	(0.031)	(0.025)
Constant	0.000	−0.875***	0.000	−0.732***
	(0.028)	(0.114)	(0.029)	(0.108)
Observations	1,113	1,113	1,113	1,113
Country FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
R-squared	0.144	0.340	0.046	0.406

Notes: Robust Ses are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% level.

find that these institutional settings are either negative or non-significant predictors of innovation.

4.4. Robustness tests

4.4.1. Alternative principal component specification

In this section, we provide robustness tests for the empirical analysis above. First, considering the existence of several methodologies of principal components' selection, we test selection bias arising from the adoption of the Kaiser (1961) criterion. Therefore, we use two of the most popular alternative selection criteria: the rule of thumb for selecting principal components explaining 70 percent of the sample variance and the Cattell (1966) selection criterion, which uses the first flex points in the principal component's scree plot as the threshold for the components' selection. In our data setting, the 70 percent variance test leads us to include five principal components rather than four. Using the Cattell (1966) selection criterion, we end up with just the first three principal components. Overall, we re-perform our baseline regressions using the two mentioned methods (see Table 8, and Table 9) and conclude that our findings remain qualitatively unchanged in all the specifications[13].

4.4.2. Different measures of green innovation

Second, we re-run our baseline model, substituting the dependent variable and replacing it with total patents (either granted by the European Patent Office (EPO) or other main patent offices). The aim of this robustness test is twofold. First, considering all patents, instead of only green patents, can help us understand if there is any difference between institutional models' performance across different types of innovation in the innovation sphere. Put differently, this test allows a direct comparison of our results relating to green innovation to total innovation (in all fields). Second, this regression also facilitates the comparison of our results with the findings of the relevant Varieties of Capitalism literature (e.g., Witt and Jackson, 2006; 2016, among others), performing an analysis similar to this one, thus understanding the performance of our institutional components. Again, the results are qualitatively identical; LMEs appear more prolific with respect to patents, both in all fields and in environmental innovation. This is consistent with our first hypothesis (see Table 10).

4.4.3. Non-market strategies as a mediator of the effect of institutions on proclivity to innovate

In the Online Appendix A.5, we test whether non-market strategies such as lobbying, which, for example, is well known in the oil and gas industry (Andreou & Kellard, 2021), affect the institutional settings in which green innovation occurs. We do so by testing whether controlling for countries' level of corruption, most likely facilitating the impact of lobbying activity on government policy, our results remain robust and whether lobbying activity, in general, affects the level of innovation. We perform two tests for this phenomenon.

First, we add to our baseline regression (1) an index of domestic corruption (the CPI, see Online Appendix A.5) both individually and interacted with our institutional settings explanatory variables. Our baseline results are unaffected. Moreover, we observe that lobbying is detrimental to green innovation in more coordinated (government-reliant) countries (CMEs). In other words, it seems that non-market strategies have a bigger effect in CMEs, which is not what would be expected; perhaps because non-market strategies are so common in LMEs, that they have diminishing returns (existing literature says that it is indeed associated with it – Jean et al., 2016).

Second, using the same regression set-up, we interact our variables of capitalism with a dummy variable ('Corrupt'), taking a value of 1 when the CPI is greater than the national median of the CPI index. Once again, our results remain robust and yield the same conclusions as the previous robustness regression.

4.4.4. Additional tests

As stated by Hsu et al. (2014) and in line with our baseline regression findings, capital market development often produces a large positive effect on innovation compared with credit market developments. Since we do not explicitly explore the importance of credit markets, it is necessary to see if the omission of information potentially captured in this variable leads to overestimating the importance of our principal components.

To account for this, we collect from the WorldBank database information on countries' bank credit availability (proxied by total bank credit-to-GDP) for the countries and years of analysis and assess whether including this variable has any effect on the significance and sign of our main explanatory variable. We show the results of this test in Table XV of the Online Appendix A.5, highlighting that our results are robust to the inclusion of proxies for credit market conditions.

Ultimately, given our PCA's parsimoniousness, we perform a DeBenedictis-Giles (1988) RESET test to ensure our results do not suffer from any omitted variable bias (see, DeBenedictis et al., 1998). We show the results in Online Appendix A.6, confirming that our baseline regressions do not display omitted variable bias.

4.4.5. Non-disclosed robustness tests

We also performed several additional tests, and their results are not disclosed in this section but are available upon request. Among these, we tested the robustness of our baseline model to the exclusion of the United States – given its importance among LMEs in terms of innovation output (c.f. Taylor (2004) and Figs. 1 and 2). We tested the performance of our original Principal Component Regression

[13] Tables 8 and 9 show the robust estimation of (1). Likewise, the empirical results are qualitatively similar when performing these robustness tests on our regressions displayed in equations (2) and (3). Results omitted to save space but available on request from the authors.

Table 8
Explaining green innovation – principal component regression using the 70 percent variance criterion Table 8 displays the results of our baseline principal component regression of the percentage of green patents in the mix (columns 1–2), the relative advantage in green technologies (columns 3–4), the percentage of green technologies (columns 5–6), the number of firms involved in the UN Global Compact (columns 7–8), on our institutional principal components. The regression results presented in this Table are obtained by adopting the 70 percent variance criterion to select the principal components. All regressions contain either country fixed-effects or country fixed-effects and time-fixed effects. Further in-depth information on the variables included in this Table is reported in Appendix A.1.

	(1) *green_tech_perc*		(2) *rel_adv_env*		(3) *env_inv*		(4) *subs_GC*	
Dim1 (CME)	−0.098*	−0.138***	−0.124**	−0.137**	0.146***	0.129***	−0.054	−0.003
	(0.051)	(0.046)	(0.052)	(0.053)	(0.051)	(0.045)	(0.052)	(0.021)
Dim2 (LME)	0.189***	0.028	0.120***	0.092*	0.264***	0.136***	0.106**	0.016
	(0.044)	(0.043)	(0.044)	(0.051)	(0.044)	(0.043)	(0.044)	(0.020)
Dim3 (CDE)	−0.079**	0.050	0.045	0.041	−0.173***	−0.054	−0.158***	0.025
	(0.040)	(0.036)	(0.040)	(0.042)	(0.040)	(0.036)	(0.040)	(0.017)
Dim4 (ALME)	0.007	−0.007	0.013	0.012	−0.002	−0.014	−0.003	0.005
	(0.032)	(0.028)	(0.032)	(0.032)	(0.031)	(0.027)	(0.032)	(0.013)
Dim5	−0.184***	−0.065	−0.129**	−0.123**	−0.044	0.050	−0.091	−0.008
	(0.056)	(0.050)	(0.056)	(0.058)	(0.055)	(0.050)	(0.056)	(0.023)
Dim6	0.018	−0.008	−0.003	−0.017	0.002	−0.023	−0.003	0.025
	(0.046)	(0.040)	(0.046)	(0.046)	(0.045)	(0.039)	(0.046)	(0.018)
Constant	−0.000	−0.757***	0.000	−0.009	−0.000	−0.762***	0.000	−0.940***
	(0.030)	(0.119)	(0.030)	(0.138)	(0.029)	(0.118)	(0.030)	(0.055)
Obs	1,113	1,113	1,113	1,113	1,113	1,113	1,113	1,113
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.031	0.298	0.022	0.049	0.055	0.310	0.021	0.849

Notes: Robust Ses are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% level.

Table 9
Explaining green innovation – principal component regression using Cattell's (1966) selection criterion Table 9 displays the results of our baseline principal component regression of the percentage of green patents in the mix (columns 1–2), the relative advantage in green technologies (columns 3–4), the percentage of green technologies (columns 5–6), the number of firms involved in the UN Global Compact (columns 7–8), on our institutional principal components. The regression results presented in this Table are obtained by adopting the Cattell (1966) principal component selection criterion. All regressions contain either country fixed-effects or country fixed-effects and time-fixed effects. Further in-depth information on the variables included in this Table is reported in Appendix A.1.

	(1) *green_tech_perc*		(2) *rel_adv_env*		(3) *env_inv*		(4) *subs_GC*	
Dim1 (CME)	−0.098*	−0.136***	−0.124**	−0.134**	0.146***	0.128***	−0.054	−0.003
	(0.051)	(0.046)	(0.052)	(0.053)	(0.051)	(0.045)	(0.052)	(0.021)
Dim2 (LME)	0.186***	0.021	0.120***	0.075*	0.264***	0.151***	0.107**	0.008
	(0.043)	(0.042)	(0.044)	(0.043)	(0.043)	(0.041)	(0.044)	(0.019)
Dim3 (CDE)	−0.076*	−0.058*	0.045	0.060	−0.172***	−0.068**	−0.159***	0.032
	(0.039)	(0.034)	(0.040)	(0.040)	(0.039)	(0.034)	(0.040)	(0.016)
Constant	0.006	−0.771***	0.013	−0.038	−0.002	−0.746***	−0.003	−0.945***
	(0.031)	(0.118)	(0.032)	(0.137)	(0.031)	(0.117)	(0.032)	(0.055)
Observations	1,113	1,113	1,113	1,113	1,113	1,113	1,113	1,113
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.031	0.296	0.022	0.045	0.055	0.310	0.021	0.849

Notes: Robust SEs are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% level.

without interpolating the missing observations. We also regressed individual institutional variables in a random-effects panel regression. The random effect model is an obvious choice, considering the many time-invariant variables included in our regression model. That said, we have also further validated that choice using the Hausman test. All results provide evidence of the reliability of our findings and are available on request.

5. Conclusion

In this paper, we first examine which economies, institutional and financial contexts are better suited to the generation of green innovation. Employing a novel and large dataset, we show that Liberal Market Economies (LMEs) outperform Coordinated Market Economies (CMEs) in the generation of green innovation. More specifically, we provide evidence that liberal types of capitalism, associated with greater financial market depth and shareholder protection, have better institutional features and corporate culture to foster green innovation. Moreover, once we compare green innovation with innovation in all domains and technologies, the result is confirmed, with no significant differences. Indeed, it would appear that LMEs present a better institutional framework for innovation *per se*, which would suggest a continuation of the traditional advantages of this type of economy (see Taylor, 2004; Becker, 2009;

Table 10
Principal component regression performed on total patents Table 10 displays the results of our baseline principal component regression of the total (all) patents from the European Patent Office (columns 1–2) and total (all) patents from all patent offices (columns 3–4) on our institutional principal components. All regressions contain either country fixed-effects or country fixed-effects and time-fixed effects. Further in-depth information on the variables included in this Table is reported in Appendix A.1.

	(1) *total patents EPO*		(2) *total patents all offices*	
Dim1 (CME)	0.320***	−0.055*	0.177***	0.035
	(0.047)	(0.030)	(0.048)	(0.045)
Dim2 (LME)	0.496***	−0.037	0.439***	0.160***
	(0.040)	(0.033)	(0.041)	(0.041)
Dim3 (CDE)	−0.186***	−0.021	−0.248***	−0.143***
	(0.036)	(0.027)	(0.037)	(0.033)
Dim4 (AMLE)	0.031	−0.003	0.013	−0.010
	(0.029)	(0.021)	(0.029)	(0.026)
Constant	0.000	−0.846***	0.000	−0.993***
	(0.027)	(0.093)	(0.028)	(0.115)
Observations	1,113	1,113	1,113	1,113
Country FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
R-squared	0.162	0.337	0.132	0.564

Notes: Robust SEs are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% level.

Boschma & Capone, 2015).

Hence, we would agree with Hsu et al. (2014) findings on the relative impact of capital market development versus bank-based financial systems on innovation; this would be broadly in line with the literature on comparative capitalism (c.f. Hall and Soskice, 2001). However, within this general picture, there are subtle variations. For example, earlier work highlights how LME firms are much better at coming up with radical innovations than implementing incremental ones; the converse is true with CMEs (Casper and Whitley, 2004). Again, bank-based financial systems might be more conducive to the implementation of green innovations, given the longer time horizons and less dynamic revenue flows associated with the latter (Allen et al., 2021; Doh et al., 2021; Wood, 2018). This study empirically confirms this relationship on a comparative basis and seeks to deepen our theoretical understanding of the same.

More specifically, the generation of green innovation does not imply its application by firms, and it is the very employment of such innovation that will aid the achievement of the United Nations Sustainable Development Goals. This leads us to the second main finding, that in applying green innovation – embedding sustainability in business practices – CMEs (where financial actors are less demanding of higher short-term returns) perform significantly better than LMEs. This would suggest that the operationalisation of green technologies will not necessarily address the challenges of industrial decline encountered in LMEs, even if they are superior in terms of coming up with new ideas in the first place. In the case of emerging markets, Ambiguous Liberal Market Economies (ALMEs) are particularly associated with poor performance in terms of the adoption of green innovations, most notably when compared to the impressive performance of Coordinated Developing Economies (CDEs).

We also acknowledge the methodological limitations arising from modelling complex national institutional frameworks. The lack of a widely accepted index for capitalist diversity in emerging markets and the ongoing development of comparative capitalism theories provide a challenge for those studies using a single method. The Varieties-of-Capitalism (VOC) approach continues to be highly effective in summarising and addressing this complexity. However, many scholars employ different categories and methodologies. For instance, Hall and Soskice (2001) defined two discrete main categories of capitalism; Amable (2003) identified five types; Witt and Jackson (2016) four, and so on. The identification challenge is frequently solved using arbitrary theoretical considerations or data aggregation (or data reduction) techniques such as factor analysis, principal component analysis, or similar (see Hall and Gingerich, 2009; Amable, 2003; Witt and Jackson, 2016). Our paper employs principal component analysis, allowing the use of a parsimonious dataset in our regression models and not relying on *a priori* assumptions related to dataset structure (Chatfield and Collins, 2000:88).

Given the results, we propose that the long energy transition might result in the current differences between firms operating in different types of capitalism, and their financial markets may persist in the future or even become more pronounced. This challenges earlier predictions that such differences will diminish over time (c.f. Streeck, 2009). In policy terms, this supports the notion that specific national institutional regimes and, by implication, the relative incentives and power they accord to investors mould firm-level practice. This study highlights that whilst liberal markets may be superior in generating green innovations, they suffer from the same challenges in implementing them as with more traditional technologies. In other words, hopes of a green industrial revolution may be premature unless there is substantive regulatory intervention. We would urge policymakers to reconsider the appropriate mix of emissions trading schemes, carbon taxation and green subsidies at both a supranational and country level. For example, recent work such as Bai and Ru (2022) shows that emission trading schemes reduce greenhouse gas emissions, in part by improving the use of renewable energy. Finally, the implementation of green innovations may impact back on the financial system and investor behaviour. In an age where the recapitalisation of firms through central bank financing has become widespread, there are many opportunities to prioritise firms that implement green innovations, enticing investors to take such firms more seriously.

Finally, this paper opens up several avenues for future research. We suggest that a priority could be to explore a range of specific innovations in environmental sustainability and how these vary according to national institutional domains and their financial systems, and, indeed, categories of investors. Moreover, although we also explore the effect of lobbying as an example of non-market strategies, there might well be other moderator and mediator variables that can help further explore the mechanisms through which different countries' institutional settings, financial markets, regional innovation systems, and/or industry dynamics, might impact on the level of adoption of green innovations. A further avenue might be the exploration of the effect of cross-border spillovers of green technologies, financing and related knowledge that will be of pivotal importance to support policymakers in ensuring a green transition.

CRediT authorship contribution statement

Neil M. Kellard: Conceptualization, Supervision, Formal analysis, Investigation, Methodology, Project administration, Resources, Validation, Writing – original draft, Writing – review & editing. **Alexandros Kontonikas:** Conceptualization, Supervision, Formal analysis, Investigation, Project administration, Resources, Validation, Writing – original draft, Writing – review & editing. **Michael J. Lamla:** Conceptualization, Supervision, Formal analysis, Investigation, Project administration, Resources, Validation, Writing – original draft, Writing – review & editing. **Stefano Maiani:** Conceptualization, Data curation, Software, Visualization, Formal analysis, Investigation, Project administration, Resources, Validation, Writing – original draft, Writing – review & editing. **Geoffrey Wood:** Conceptualization, Supervision, Formal analysis, Investigation, Project administration, Resources, Validation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intfin.2023.101853.

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