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Essays on the nexus between technological change, policies, and value chain governance for a transition towards a low-carbon economy

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To

María Emilia and Felipe

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Abstract

Technological change is essential to reconciling economic growth with environmental conservation. A transition toward an environmentally sustainable economic system requires new production techniques that improve land use efficiency, increase yields, reduce chemical input applications, prioritize low-carbon energy sources, and integrate new (non-fossil) raw materials. However, even when technical change promises to safeguard environmental sustainability, it is not a sufficient condition to reach inclusive growth since it is non-neutral from a social perspective. Balancing multiple goals to ensure a just transition requires consistency between governing institutions and technological advances, which is a two-way relationship: some governance schemes may be more conducive to fostering technical change, whereas new governance patterns and institutions emerge in response to innovations. This Ph.D. dissertation explores the nexus between technical change, policies, and value chain governance from different points of view in three separate chapters, each focusing on a different technology set: bio-based technologies, technological innovations in agri-food systems, and renewable energy.

In the first chapter, I explore from a conceptual perspective the nexus between organizational characteristics of bio-based value chains and technological innovations in the transition to a bioeconomy. Moving away from the fossil-based production paradigm into a bio-based economy that creates economic value added with minimum environmental impacts requires substantial investments in technological innovations. These innovations will likely affect how value chains are structured and which actors benefit from this transformation. Accelerated bioeconomy innovation is associated with shorter and more vertically coordinated value chains, a leading role by dominant firms, and higher levels of cooperation among firms with core research capabilities. These organizational features entail welfare effects for value chain actors, leading to potential trade-offs between greenhouse gases (GHG) emissions mitigation and social inclusion.

In the second chapter, I discuss the entrepreneurial landscape of innovations that promise to revolutionize agri-food systems, covering the entire value chain from farming inputs to last-mile delivery. Using Crunchbase as the primary data source and applying machine learning for natural language processing, the purpose of this chapter is twofold: first, identify which technologies have been receiving the most support from investors, and second, analyze the corporate strategies of the largest agri-food multinational companies regarding their investments in new technologies. The results for the first goal show an imbalanced scene in which downstream technologies capture most investors' interest. As for the second goal, three trends of investments by dominant agri-food firms are identified: upgrading strategies to improve their core activities, defensive strategies to control technologies that compete with their business, and corporate portfolio strategies to seize profit opportunities.

Given that the adoption of many clean technologies is still low in many regions of the world, in the third chapter, I delve into the role of policy design in fostering technology adoption to reach low-carbon production systems. For this purpose, I focus specifically on studying how institutional quality and macroeconomic instability mediate the effects of auctions in promoting investments in renewable energy technologies. The analysis is built upon a differences-in-differences analysis considering staggered treatment adoption. Findings show that auctions positively affect RE capacity, but average treatment effects are higher for countries with better business environments. Thus, caution is needed in adopting this instrument, especially in countries exposed to macroeconomic or institutional

instability. At the same time, dynamic treatment effects suggest that the policy needs time to show results.

Based on the findings in this study, policymakers should account for the fact that the surrounding governing institutions condition the effects of technical change over different sustainability dimensions. While synergies between economic and social dimensions are more evident, balancing these two dimensions and environmental goals is not always straightforward and requires fine-tuning in policy design. From the perspective of business managers and entrepreneurs, it is essential to acknowledge that new value chains will emerge, and the traditional ones will reconfigure, opening new business opportunities in which sustainability aspects are at the core of the strategy.

Zusammenfassung

Der technologische Wandel ist von entscheidender Bedeutung, um Wirtschaftswachstum und Umweltschutz in Einklang zu bringen. Der Übergang zu einem ökologisch nachhaltigen Wirtschaftssystem erfordert neue Produktionstechniken, die die Effizienz der Flächennutzung verbessern, die Erträge steigern, den Einsatz von Chemikalien reduzieren, kohlenstoffarme Energiequellen bevorzugen und neue (nicht-fossilen) Rohstoffe integrieren. Doch selbst wenn der technische Wandel verspricht, die ökologische Nachhaltigkeit zu sichern, ist er keine hinreichende Bedingung, um ein integratives Wachstum zu erreichen, da er aus sozialer Sicht nicht neutral ist. Um einen gerechten Übergang zu gewährleisten, müssen mehrere Ziele miteinander in Einklang gebracht werden, was eine wechselseitige Beziehung zwischen den Regierungsinstitutionen und dem technologischen Fortschritt voraussetzt: Einige Regierungssysteme können den technischen Wandel eher fördern, während sich neue Regierungsmuster und Institutionen als Reaktion auf die Innovationen herausbilden. Diese Dissertation untersucht den Zusammenhang zwischen technischem Wandel, Politik und Governance in der Wertschöpfungskette aus verschiedenen Blickwinkeln in drei separaten Kapiteln, die sich jeweils auf einen anderen Technologiebereich konzentrieren: biobasierte Technologien, technologische Innovationen in der Agrar- und Ernährungswirtschaft und erneuerbare Energien.

Im ersten Kapitel untersuche ich aus einer konzeptionellen Perspektive den Zusammenhang zwischen den organisatorischen Merkmalen biobasierter Wertschöpfungsketten und technologischen Innovationen beim Übergang zu einer Bioökonomie. Die Abkehr vom fossilen Produktionsparadigma hin zu einer biobasierten Wirtschaft, die einen wirtschaftlichen Mehrwert bei minimalen Umweltauswirkungen schafft, erfordert erhebliche Investitionen in technologische Innovationen. Diese Innovationen werden sich wahrscheinlich darauf auswirken, wie die Wertschöpfungsketten strukturierten sind und welche Akteure von diesem Wandel profitieren. Eine beschleunigte Innovation in der Bioökonomie geht mit kürzeren und stärker vertikal koordinierten Wertschöpfungsketten, einer führenden Rolle dominanter Unternehmen und einem höheren Maß an Zusammenarbeit zwischen Unternehmen mit Forschungskapazitäten einher. Diese organisatorischen Merkmale bringen Wohlfahrtseffekte für die Akteure der Wertschöpfungskette mit sich und führen zu potenziellen Kompromissen zwischen der Verringerung der Treibhausgasemissionen und der sozialen Integration.

Im zweiten Kapitel erörtere ich die unternehmerische Landschaft von Innovationen, die eine Revolutionierung der Agrar- und Ernährungssysteme versprechen und die gesamte Wertschöpfungskette von den landwirtschaftlichen Betriebsmitteln bis zur letzten Meile abdecken. Unter Verwendung von Crunchbase als primäre Datenquelle und der Anwendung von maschinellem Lernen für die Verarbeitung natürlicher Sprache verfolgt dieses Kapitel zwei Ziele: Erstens soll ermittelt werden, welche Technologien die meiste Unterstützung von Investoren erhalten, und zweitens sollen die Unternehmensstrategien der größten multinationalen Unternehmen der Agrar- und Ernährungswirtschaft hinsichtlich ihrer Investitionen in neue Technologien analysiert werden. Die Ergebnisse für das erste Ziel zeigen eine unausgewogene Szene, in der nachgelagerte Technologien das meiste Interesse der Investoren auf sich ziehen. Was das zweite Ziel betrifft, so lassen sich drei Trends bei den Investitionen marktbeherrschender Agrar- und Lebensmittelunternehmen erkennen: Modernisierungsstrategien zur Verbesserung ihrer Kernaktivitäten, defensive Strategien zur Kontrolle von Technologien, die mit ihrem Geschäft konkurrieren, und Unternehmensportfolio-Strategien zur Nutzung von Gewinnchancen.

In Anbetracht der Tatsache, dass die Einführung vieler sauberer Technologien in vielen Regionen der Welt immer noch gering ist, befasse ich mich im dritten Kapitel mit der Rolle der politischen Gestaltung bei der Förderung der Einführung von Technologien, um kohlenstoffarme Produktionssysteme zu erreichen. Zu diesem Zweck konzentriere ich mich speziell auf die Frage, wie institutionelle Qualität und makroökonomische Instabilität die Auswirkungen von Auktionen auf die Förderung von Investitionen in erneuerbare Energietechnologien beeinflussen. Die Analyse basiert auf einer Differenzen-in-Differenzen-Analyse, die eine gestaffelte Einführung der Behandlung berücksichtigt. Die Ergebnisse zeigen, dass sich Auktionen positiv auf die EE-Kapazität auswirken, aber die durchschnittlichen Behandlungseffekte sind in Ländern mit einem besseren Geschäftsumfeld höher. Daher ist bei der Anwendung dieses Instruments Vorsicht geboten, insbesondere in Ländern, die einer makroökonomischen oder institutionellen Instabilität ausgesetzt sind. Gleichzeitig deuten die dynamischen Behandlungseffekte darauf hin, dass die Politik Zeit braucht, um Ergebnisse zu zeigen.

Basierend auf den Ergebnissen dieser Studie sollten politische Entscheidungsträger die Tatsache berücksichtigen, dass die Auswirkungen des technischen Wandels abhängig sind von den verschiedenen Nachhaltigkeitsdimensionen von den umgebenden Institutionen. Während Synergien zwischen wirtschaftlichen und sozialen Dimensionen offensichtlicher sind, ist es nicht immer einfach, ein Gleichgewicht zwischen diesen beiden Dimensionen und den Umweltzielen herzustellen, und erfordert eine Feinabstimmung bei der Politikgestaltung. Aus der Sicht von Managern und Unternehmern ist es wichtig anzuerkennen, dass neue Wertschöpfungsketten entstehen und sich die traditionellen Wertschöpfungsketten umgestalten werden, was neue Geschäftsmöglichkeiten eröffnet, bei denen Nachhaltigkeitsaspekte im Mittelpunkt der Strategie stehen.

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List of Abbreviations

2SDID	Two-stage difference-in-differences estimator
AFS	Agri-food systems
ATT	Average treatment effect on the treated
CO_2	Carbon dioxide
CS	Callaway and Sant'Anna difference-in-differences estimator
COVID	Coronavirus disease
IADB	Inter-American Development Bank
IMF	International Monetary Fund
IRENA	International Renewable Energy Agency (IRENA)
DiD	Difference-in-differences
FDI	Financial Development Index
FPR	False positive rate
GDP	Gross domestic product
GHG	Greenhouse gas
GVCs	Global value chains
IP	Intellectual property
LASSO	Least absolute shrinkage and selection operator
LDA	Latent Dirichlet allocation algorithm
NB	Naïve Bayes
ML	Machine learning
NLP	Natural language processing
PCA	Principal component analysis
R&D	Research and Development
RE	Renewable energy
ROC AUC	Area under the receiver operating characteristics curve
SVM	Support vector machine
TPR	True positive rate
TWFE	Two-way fixed effects
USD	United States dollars

Introduction

Motivation and background

Global warming, biodiversity loss, and several other environmental impacts from anthropogenic activities have pushed our earth systems to the limit. Without globally coordinated and targeted measures, the environment heads toward a no-return point (Steffen et al., 2018). Despite projected climate scenarios showing that our current trajectory would lead to alarming consequences for human health, species conservation, and food production (IPCC, 2023), governmental commitment in terms of mitigation has been insufficient. Policy actions have not shown enough determination, considering that only substantial cuts to current and future greenhouse gases (GHG) emissions will lead to scenarios of achievable 1.5-2 degrees temperature limits. Moreover, the climatic crisis entails multiple social consequences since it is expected to impact severely on the poorest: research has linked climate change to an increase in the gap between rich and poor countries (Diffenbaugh & Burke, 2019) and to a reduction in agricultural productivity that challenges countries experiencing severe food insecurity (Ortiz-Bobea et al., 2021; Wing et al., 2021).

In the last two centuries, anthropogenic activities have been the main driver of the boost in GHG emissions and environmental degradation (Crippa et al., 2021; Lamb et al., 2021). However, economic growth (coupled with accurate and well-targeted social policies) is still needed to improve livelihoods, eradicate poverty, and reduce inequalities (CEPAL, 2022). In spite of the improvements observed in poverty rates at a global level, there are still severe regional disparities: some regions have managed to bring most of their population above poverty lines, whereas other regions still struggle to ensure minimal livelihoods (Kharas & Dooley, 2022). Moreover, the income gap between the top 1% and the lowest strata have broadened (Alvaredo et al., 2018). Within a framework of triple-bottom-line sustainability, synergies between economic and social dimensions are attainable, but trade-offs exist between socioeconomic and environmental goals (Barbier & Burgess, 2019; Pradhan et al., 2017). Therefore, new strategies are needed to promote inclusive economic growth within planetary boundaries.

Technological change in front of climate change

Technological change is critical to reconciling growth with conservation goals (Herrero et al., 2020). Some strategies to minimize the environmental side-effects of the economic system require behavioral changes such as migrating to more sustainable consumption patterns (Costa et al., 2022) or changing corporate behavior toward more sustainable practices (Sellare et al., 2022). However, despite the necessary changes in behavior, economic growth within planetary boundaries requires shaking the technological foundations of the current production paradigm (Mehmood et al., 2023; F. Wang et al., 2021). A bio-based economy, founded on the revalorization of the natural capital for the creation of economic and social value, entails innovations for the sustainable use of renewable resources and is presented as a pathway toward the achievement of sustainable development goals (El-Chichakli et al., 2016; Zilberman, 2014). This transition toward an environmentally sustainable economic system requires new production functions that increase land use efficiency, reduce input needs, prioritize low-carbon energy systems, and adopt new (non-fossil) raw materials. These simultaneous transformations across every economic sector potentially imply a technological revolution (Mazzucato & Perez, 2023).

Technological disruption is not a completely novel phenomenon. Humanity has experienced different waves of industrial change over the last 200 years, from the first industrial revolution based on mechanization and steam power to the most recent industrial revolution based fundamentally on information and telecommunications (Perez, 2010). Now, it seems that the environmental crisis is urgently pushing innovations and becoming the potential driver for a change in the technical paradigm (S. Barrett, 2009; Hockfield, 2019), which implies cross-sectoral changes at many levels of the economy and synergies among technologies (Mazzucato & Perez, 2023). The last decade has presented us with a dynamic trend of technical change in three converging and synergic fields: advances in life sciences that allow more efficient ways of modifying the genetic code (Chui et al., 2020; J. Y. Wang & Doudna, 2023), the exponential acceleration of artificial intelligence and robotics (Gent, 2020; Stokel-Walker & Van Noorden, 2023) and the massive adoption of digitalization technologies (Verhoef et al., 2021). The convergence between these three fields promises several applications to cut GHG emissions and contribute toward cleaner and more sustainable production systems.

Economists have approached economic growth and technical change in the context of climate change from several perspectives. Some of these approaches treat technology as exogenous. For example, Nordhaus (2007) considers the changes in factor productivity dependent on a single technological parameter that evolves over time. This model suggests a trade-off between consumption now and consumption in the future and advocates for low and gradual interventions in which a carbon pricing setting delivers optimal results (Aghion et al., 2019). However, models that endogenize technical change in climate policy models seem more realistic. Gillingham et al. (2008) summarize three different alternatives for such purpose. The first is related to direct-price-induced technical change, in which technical change will be oriented to reduce the use of the relatively more expensive factor (i.e., if energy prices rise, innovation will be oriented either to streamline energy efficiency or to develop alternative power sources) (Popp, 2004). However, this type of model still considers innovation as an aggregated phenomenon that takes place for the overall economy, disregarding sectoral trends or enterprise behavior (Aghion et al., 2019). A second approach is learning-induced technical change (Gillingham et al., 2008). This is related to the development by Rosenberg (1983), who analyzes the processes inside the firms and claims each innovation creates a necessity for further innovations by suppliers. At the same time, the costs of a technology decrease with its use due to a learning process by the company and its suppliers.

The third approach, which has gained more attention recently, is related to research and development (R&D) induced technical change. Acemoglu (2012) presents a two-sector model, one intensive in dirty production factors and the other based on clean technologies. The dirty sector, dominant in the beginning, enjoys cost advantages since all the infrastructure in the economy supports the use of such dirty technologies. Thus, innovation tends to favor that sector. Regulatory measures based on carbon taxes or research subsidies may help to redirect technical change in favor of clean technologies. This model calls for immediate actions since regulatory delays involve substantial environmental costs, given that both technologies are highly substitutable. However, those regulatory interventions may be only needed temporarily: once clean technologies have the right set of incentive levels, price and market size effects will naturally reconduct innovation toward them (Acemoglu et al., 2012).

The challenges of an innovation-driven paradigm change

Acknowledging that R&D can steer technical change toward clean technologies leads to the question of what drives R&D investments and what determines the orientation of R&D efforts. What lines of basic research are prioritized or which applications are developed using that research do not come as exogenous choices and are highly conditioned by the predominant technological paradigm. This is the idea behind the concept of path dependency, which is one of the main challenges for an innovation-driven paradigm change toward an economic system within planetary boundaries. R&D is itself an endogenous process for two reasons. First, research efforts (and funds) prioritize technologies that leverage already existing technologies. Second, final users find switching to a different technology unattractive at the beginning (Aghion et al., 2019). The combination of these two facts creates a path dependency in which the current technological paradigm sets boundaries for prospective research. Compared to the fossil-based dominant paradigm, built upon both mature technologies and mature markets, ventures focused on decarbonization depend on R&D activities whose success is not guaranteed and might face higher capital and operational costs.

Some authors have recently pointed out that regulation or simple intervention to fix market failures (as proposed by endogenous growth models) is not enough, and more stout and comprehensive measures are needed to break path dependency and inertia in the research system. These ideas reappraise the institutional dimension behind innovation and point out the need to create new markets and governance schemes for a clean transition (Mazzucato, 2016). There are many market uncertainties in a technological transition, such as finding long-term capital to fund R&D, establishing new relationships with clients, suppliers, and partners, figuring out the optimal scales of production and its associated cost levels, setting optimal mechanisms for knowledge and technology transfer and designing adequate value chain governance schemes, just to mention a few of them. The creation of new markets and networks of actors is crucial in unveiling these unknowns during a technological transition, reducing the risk level for private investments, and creating the conditions for the diffusion of innovations. Simultaneous and synergic changes are needed at different levels, with a mission-oriented approach aligning efforts in the public and private sectors (Mazzucato, 2018).

These efforts to build new markets and new institutions toward decarbonization should also prioritize the social dimension. Innovation-driven sustainable growth needs to be also inclusive growth. Directed technical change models have highlighted that technological change may favor skilled labor against unskilled labor, increasing inequality gaps (Acemoglu, 1998, 2002). The higher needs of skilled labor promoted by new technologies do not imply a reduction in the factor retribution of skilled workers in the long run (Jones & Romer, 2010). However, skilled-biased technical change is not the one and single explanation of inequalities associated with the innovation process. Mazzucato and Perez (2023) highlight that losers in an industrial revolution (i.e., companies and workers that lose a central position in the economic system) cannot quickly re-specialize into the new technical paradigm and are kicked out of the system. Furthermore, Lazonick and Mazzucato (2013) point out that the excessive financialization that comes with technological revolution might assign financial actors a higher share of the reward of the innovation success over other actors such as workers, taxpayers, or the scientific sector. Finally, uneven access to innovations may also be a source of increasing inequalities (Lythreatis et al., 2022).

In summary, I have presented two main ideas in this section. First, technical change toward cleaner production technologies is indispensable to address the current environmental crisis while promoting economic growth. Second, technological innovation needs to be paired up with a proper set of incentives through the implementation of accurate governance schemes and the creation of new markets that help to (a) overcome path dependencies of a fossil-dependent economy that may hinder the deployment of these innovations, and (b) safeguard the social dimension in the technological transition to reach genuinely inclusive growth. Thus, balancing multiple goals and ensuring a just transition requires combining political and sociocultural changes tied to technological advances (C. B. Barrett et al., 2020). Innovation in institutions and governance schemes needs to go hand-in-hand with technical innovation: the quality of the surrounding macro-level institutions in society may foster or hinder technical change, but at the same time, it must change in response to innovations. In this dissertation, I explore three strands of technologies with a sustainability purpose and two governance levels: private-led in value chains and public-led in policy design.

Goals and research questions

This work is part of a larger project called **"Transformation and Sustainability Governance in South American BioEconomies"** (SABio) that seeks to inform public and private actors in South America and beyond "*about entry points for action towards promoting climate-smart bio-based innovation processes that safeguard rural employment and the equitable distribution of the benefits and costs of bio-based transformation"* (Sabio Project, 2020). This dissertation belongs to the Agricultural Economics group at the University of Bonn and addresses the nexus between technological change, policies, and value chain governance for a transition towards a low-carbon economy, with three main research goals, each of them addressed by the three separate chapters:

The *first research goal* is to understand the role of value chains in fostering bioeconomy innovation, exploring how the organizational aspects of value chains relate to technological innovations in the transition to a bioeconomy. This way, I contribute to understanding how technological and institutional innovations can shape market structures and the organization of value chains. The research questions in this first chapter are: (1) Which value chain features may be more conducive to a process of bioeconomy upgrading? And (2) in what way do the organizational characteristics of these new value chains may affect the social sustainability dimension in the face of a bioeconomy upgrading?

The *second research objective* is to analyze the links between technological innovations related to food production, distribution, and consumption and the industry structure in agri-food global value chains (GVCs). Specifically, I study the entrepreneurial landscape of innovation in agri-food systems (AFS), covering the entire value chain (from farming inputs to last-mile delivery) while introducing the perspective of corporate venture capital. This way, I explore the potential influence of industry concentration in the transition toward more sustainable agri-food GVCs, discussing the role of dominant firms in shaping new technological solutions developed by start-up firms. The goal is reflected in the following research questions: (1) what are the leading technologies and solutions entrepreneurs are taking to the market in agri-food value chains? and (2) what type of investments are incumbent agri-food companies prioritizing as venture capitalists?

The *third research goal* is to understand the role of policy design in reaching low-carbon energy systems. I focus on renewable energy (RE) auctions, a policy instrument that has been increasingly adopted in developing countries to promote investments in renewable while capping support costs for governments. While auctions have proven successful in developed economies, I explore in this chapter if they can still work in contexts of poor institutional quality and macro-level instability. The research questions in this chapter are: 1) Do RE auctions affect the deployment of RE in contexts of macroeconomic instability and poor institutional quality? and 2) Does the effectiveness of auctions in promoting investments in RE vary across different technologies (i.e., solar, wind, and biomass)?

The nexus between the three individual chapters

The first common point among the three chapters is that each studies different types of technological change oriented to promote environmental sustainability. The *first chapter* discusses bio-based technologies. Production technologies that require less biomass or employ higher-generation biomass sources (e.g., low-value waste streams or non-food feedstocks) are desirable to mitigate some adverse consequences of a biomass-intensive economy, mainly direct and indirect land use change. The *second chapter* explores innovations to improve global agri-food value chains. These innovations cover the whole value chain, going from farming inputs (such as bio-based inputs or digital technologies applied to farming) to final consumption (such as functional foods or last-mile delivery apps). The *third chapter* discusses RE, particularly solar, wind, and biomass technologies. These renewable sources contribute to the replacement of fossil-based electricity systems.

A second point that crosses the three chapters is the nexus between different notions of governance and technical change. The type of governance setting plays a critical role in either accelerating or hampering a sustainable transition. Governance structures comprise the rules of the game set both by public and private actors, the terms through which economic agents relate to each other, and how incentives and regulations combine to mediate economic relationships. In the *first chapter*, the focus is on governance at the value chain level, reflecting on how some organizational structures in value chains may be more conducive to fostering bio-based innovation. The *second chapter* is also related to value chain governance by discussing the role of large agri-food multinational firms in front of accelerated innovation. Agri-food GVCs have experienced a consolidation process in most stages, where now global multinational corporations play a central role in establishing governance patterns. Finally, in the *third chapter*, the prevailing aspect is the role of policies, particularly RE auctions. Many clean and renewable technologies require adequate remuneration schemes to compete against fossil-based technologies, simultaneously requiring building the proper institutional infrastructure.

A final idea underlying the three chapters is that technical change is neither a sufficient condition for the conservation of the environment nor for the inclusion of the weakest economic agents. The main point in the *first chapter* is how new bio-based value chain characteristics linked to accelerated bioeconomy innovation create trade-offs between GHG emissions mitigation and social inclusion. In the *second chapter,* the focus is on how, while many small entrepreneurs (i.e., start-up companies) can develop new solutions at the innovation supply chain level, upscaling and making them suitable for massive markets requires the commitment of incumbent firms in the product supply chain, which could enhance their dominant position in the future. In the *third chapter*, the key point is how not every policy seems suitable for countries from the global south that often face economic and institutional volatility, or at least the design of those policies needs to be adapted to the reality of each country. Government intervention and public policies are needed to change the incentives in favor of cleaner technologies, but these policies can lead to unsatisfactory results without the right design features.

Summary of methods

The *first chapter* adopts a conceptual perspective to explore the links between value chain organization and bioeconomy innovation. It starts with a narrative review of the literature on the mutual dependency between value chain characteristics and processes of innovation. I present literature explaining this twofold relationship between both categories (value chain features on the one side and characteristics of the innovation process on the other side) and extract specific dimensions that characterize each. These dimensions are used later in the second step when I present six representations that describe the organization of bioeconomy value chains. Using insights from the literature on value chain management and industrial organization, I typify activities and their vertical links across the different stages of the process of bioeconomy upgrading. Lastly, in the third methodological step, I discuss how the changing characteristics of these value chains in the context of a bioeconomy upgrading might affect income distribution for the participants. Many of the core bioeconomy innovations I discuss are not yet at a market stage, so the evidence of their distributional effects is still scarce. However, based on the available literature on value chains, I hypothesize several social sustainability implications of changes in the value chain dimension.

In the *second chapter*, I combine Natural Language Processing (NLP) tools and machine learning (ML) to classify a set of young science- and tech-based companies according to the solution these companies bring to improve global agri-food value chains. For this purpose, I work with Crunchbase, a database of technological firms that includes data on companies, people working in those companies, investors, and funding rounds. This database has been increasingly used for research in Economics and Management (Dalle et al., 2017).

First, I run a query in Crunchbase to reduce the number of companies. In this search, I identified around 26,000 potentially relevant companies. I take the description field for this set of companies to build a text corpus. I tokenize and clean the text, removing symbols, numbers, punctuations, and stopwords in English, and then build a weighted document-feature matrix, which constitutes the base for the analysis. I create a training set and classify companies according to the kind of technological solution they are developing, with the final goal of accurately predicting the class membership of each company outside the manual review sample. I applied different machine learning algorithms, such as Naïve Bayes, Support Vector Machine, and LASSO, and compared their prediction accuracy to move to the automatic classification stage based on the previously trained subset.

Finally, I list a set of large multinational corporations that are the incumbent leaders in each stage of agri-food value chains. These companies belong to different industries, such as agricultural inputs, farm machinery, commodity trading, food and beverage, and food retail. Based on our previously defined typology and classification, I analyze the founding rounds in which these companies have been involved as investors to describe their investments' direction and systematize different investment trends to explain the rationale behind their investments.

The *third chapter* aims to determine whether RE auctions are an effective mechanism for promoting investments in RE capacity in unstable business environments. For this purpose, the study draws from multiple publicly available databases to build a dataset comprising 98 countries from 2000 to 2020. The definition of RE comprises solar, wind, and biomass sources. The chapter is based on a causal inference analysis to calculate the average treatment effects of adopting auctions (considered the treatment) over the share of RE capacity (the outcome), subsetting the countries according to the quality of their business environment. I start our empirical analyses by checking to what extent self-selection might be a concern. Given the nature of the problem, I cannot assign the treatment randomly to avoid self-selection, so I explore whether countries with specific institutional or macroeconomic features are more likely to adopt auctions. Then, to incorporate the quality of the business environment in the analysis, I apply cluster and principal component analysis to reduce the dimensionality of the data and create subgroups for our research. With this approach, I end up with the business environments classified as either high or low quality.

The methodological choices of many of the quantitative studies that have analyzed RE in the past relied on two-way fixed effects (TWFE) models to evaluate the average effects of RE policies, which has been the standard approach to determining treatment effects in contexts in which not every unit receives the treatment simultaneously (known as "differential timing"). Nevertheless, TWFE regression provides biased estimations under differential timing in adoption with heterogeneous treatment effects (Goodman-Bacon, 2021). This is relevant in this case because, as countries have adopted auctions at different points in time, the policy outcomes are unlikely to be perfectly homogeneous across all countries in the sample.

Many recent developments in the difference-in-differences (DiD) methods seek to account for heterogeneous treatment effects in differential timing settings. Based on this premise, I run two models. The first DiD model I will use is the one developed by Callaway and Sant'Anna (2021). Their target parameter for identification is defined as the group-time average treatment effect. This is an extension of the ATT in the canonical 2x2 DiD but accounts for the fact that units adopt the treatment in cohorts (groups). The second DiD model applied follows a somewhat different estimation procedure. It is called two-stage DiD and was developed by Gardner (2021). Compared to CS, which works with group-time effects as building blocks for the analysis, this method follows an imputation approach, i.e., it imputes the value of the counterfactual using untreated units. Based on these approaches, I calculate the average treatment effects for each set of countries (according to the quality of the business environment) and for each technology separately.

Structure and organization of the dissertation

As described above, this Ph.D. dissertation explores the nexus between technical change, policies, and value chain governance from different points of view in three essays. Ensuring that a transition toward a low-carbon economy is also a just transition from a social perspective requires balancing and managing trade-offs between multiple policy goals. Technological advances are non-neutral regarding the political, social, and institutional spheres: some governance schemes may be more conducive to fostering technical change, whereas new governance patterns and institutions emerge in response to innovations.

The introductory chapter provides a general background and motivation for the dissertation. Chapter 1 delves into the first research goal, understanding value chain transformations in the transition to a sustainable bioeconomy. Chapter 2 examines the innovation landscape at the entrepreneurial level in global agri-food value chains, focusing on the role of incumbent firms from a corporate venture capital perspective. Chapter 3 focuses on policy aspects, studying how institutional and macroeconomic stability mediate the effect of auctions on RE capacity. The conclusion section summarizes the key findings in the dissertation and discusses policy and business implications.

Chapter 1 The nexus between innovation, value chains, and social sustainability in the context of a bioeconomy upgrading

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Abstract: The adoption of new bio-based technologies is presented as a path toward reducing greenhouse gas emissions while creating new business opportunities. But a truly sustainable transition towards a bio-based economy requires a process we define as bioeconomy upgrading, which implies moving from traditional bio-based applications that use high-volume and low-value biomass to industries built upon advanced biotechnologies that use low-volume biomass and create economic value-added while minimizing negative consequences for the environment. This process of accelerated innovations will likely affect how value chains are structured and how benefits are distributed. Yet, previous studies on the bioeconomy have ignored the relationship between value chain structure and technological change. This article analyzes the nexus between innovation, value chain characteristics, and social sustainability in the transition to a bioeconomy. We find that a bioeconomy upgrading is associated with shorter and more vertically coordinated value chains, a leading role by big firms, and higher levels of cooperation among firms with core research capabilities. Finally, we argue that while bio-based innovation can potentially achieve environmental sustainability, it creates risks for the weakest value chain actors. Thus, we propose some lines of thought regarding the potential distributional effects of bio-based innovation.

Keywords: bioeconomy, innovation, upgrading, value chains, social sustainability

1.1 Introduction

Global warming is pushing the biophysical environment towards a sustainability threshold while deepening economic inequalities (Diffenbaugh & Burke, 2019; Steffen et al., 2018). GHG emissions from energy generation, transport, and the production of food and industrial goods are the main driving forces of climate change (Lamb et al., 2021). A transition towards a bioeconomy – an economic system based on biological principles and the efficient use of sustainably produced renewable resources – is often seen as a promising strategy to reduce our reliance on fossil-based resources while promoting economic growth and striving to achieve the Sustainable Development Goals (SDGs) (Biber-Freudenberger et al., 2020; Stark et al., 2022).

This transition will require a change in the role that biomass plays in our economic system. This means moving from traditional bio-based applications that use high-volume and low-value biomass (e.g., using raw biomass to produce animal feed) to industries built upon advanced technologies that use low-volume biomass and create economic value-added while minimizing negative consequences for the environment (Bröring, Baum, et al., 2020; Kircher, 2021). We call this process a bioeconomy upgrading. This implies a paradigm shift in production, simultaneously transforming all economic sectors. Many of the most promising technologies in the bioeconomy, that apply engineering principles to life sciences, confront us with the possibility of a fifth industrial revolution, in which environmental concerns operate as the main drivers of change (Peccoud, 2016).

However, technological change does not occur in the void, disconnected from the surrounding environment: shifts in production paradigms also imply institutional and social changes (Dosi, 1982). Contextual factors (e.g., cultural patters, sociopolitical pressures) might create the demand for technological innovations that cater to niche markets at first, but then, with changes in the socio-technical regime, these innovations can be scaled-up (Geels, 2019; Geels & Schot, 2007). The socio-technical regime comprises the industrial, political, cultural, and scientific conditions that constitute the institutional setting. In this sense, technological change is not neutral, as it can favor specific production factors and actors over others (Acemoglu, 1998). Therefore, since technological change may be biased and result in a redistribution of welfare, some value chain members could see their livelihoods affected (Acemoglu, 2002).

In general terms, technical change implies that more value is added by a combination of capital and high-skilled labor, and this creates challenges, especially for low-income economies (Rodrik, 2018; Timmer et al., 2014). Introducing new technologies can also affect the organizational structure of value chains. For example, the introduction of genetically modified organisms (GMOs) has led to a reorganization of the global seed industry and a growing market concentration. This could result in higher prices for these technologies, thus affecting farmers' adoption and production costs (Deconinck, 2020). Therefore, for some members of the value chains, innovations and structural changes can bring benefits, such as price premiums, reduced costs, or new market opportunities. In contrast, other value chain members may be displaced or lose their position. This holds not only for changes in physical technology but also for institutional innovations, such as certification schemes (Sellare, 2022).

Although there is a growing number of studies on transition pathways toward a bio-based economy, this literature has largely ignored the role of value chains in fostering this process of bioeconomy upgrading. The existing analyses of the bioeconomy from a value chain perspective have focused mainly on the design of specific value chains and sectors (Carraresi et al., 2018; Cerca et al., 2022; Golembiewski et al., 2015; Mertens et al., 2019) and the emergence of new value webs around particular biomass sources (Lin et al., 2019; Loos et al., 2018; Vargas-Carpintero et al., 2022). However, these studies do not discuss in depth how the organizational characteristics of these value chains relate to technological innovations in the transition to a bioeconomy.

An explicit focus on this relationship is important because the organization of value chains has significant potential to drive technological innovations for more sustainable production systems (Swinnen & Kuijpers, 2019) and, at the same time, affect the distribution of benefits along the value chain (Minten et al., 2018). Hence, the main research questions in this chapter are: (1) Which value chain features may be more conducive to a process of bioeconomy upgrading? And (2) in what way do the organizational characteristics of these new value chains may affect the social sustainability dimension in the face of a bioeconomy upgrading?

To answer these questions, we propose an overarching conceptual framework based on six representative models of bioeconomy value chains to explore the nexus between technological innovation, value chain structures, and social sustainability in the face of an accelerated rate of bioeconomy innovation, covering not only agribusiness firms who engage in complementary bio-based market opportunities (e.g., a livestock processor who uses residues for produce animal feed) but also emerging high-tech companies that rely on low-volume and high-value biomass. We illustrate our conceptual framework with tangible and up-to-date business examples for each value chain representation.

Our study contributes to the rich body of literature that analyzes how technological and institutional innovations can shape market structures and the organization of value chains (C. B. Barrett et al., 2022; Reardon & Timmer, 2012; Zilberman et al., 2022). Our study is also complementary to the work by Zilberman et al. (2019), who present a conceptual framework to discuss how innovations used to transform feedstock from agricultural production into consumer products might affect the strategic decisions of an agribusiness firm.

The remainder of this chapter is structured as follows: Section 1.2 describes the idea of a bioeconomy upgrading in further detail. Section 1.3 explains the main points of our methodological approach. Section 1.4 presents evidence of the nexus between value chains and innovation based on previous literature. Section 1.5 offers a typology of value chain models in the bioeconomy and analyzes how they contribute to a bioeconomy upgrading. Finally, Section 1.6 discusses how some of the value chain attributes identified in the previous section may lead to different effects on the social sustainability dimension in the transition to a bio-based economy.

1.2 The process of bioeconomy upgrading

The bioeconomy is a concept that has made its way into the debate of transition pathways for complying with the Paris Agreement and achieving the SDGs (El-Chichakli et al., 2016). However, far from having an undisputed definition, different visions coexist around the bioeconomy, which seems to be a concept in constant evolution. Some of these visions focus on replacing feedstocks from the fossil-based economy with biomass (i.e., resource-based view), other visions emphasize the potential of industrial biotechnology as a pathway to intensify economic growth, while a third strand of interpretations concentrate on the potential of agro-ecological production to promote an environmentally sustainable (and locally-based) development (Bugge et al., 2016; Vivien et al., 2019).

In the public policy sphere, where many governments have presented bioeconomy strategies in the last decade (Biber-Freudenberger et al., 2018), a combination of the first two visions has been prevalent: the idea of replacing fossil-based technologies through the use of sustainably produced biomass coupled with the use of biotechnologies to promote economic growth. The United States strategy has adopted a focus on economic growth emphasizing the potential of industrial biotechnology, while the European vision (driven mainly by the German Bioeconomy Council) has placed more attention on the sustainable production of biomass tied to the concept of biorefinery (Hausknost et al., 2017; Priefer et al., 2017). Developing countries have been drawing from the experiences of the Global North and merging them with their stakeholders' interests to build local perspectives (Siegel et al., 2022). In the private sphere, companies have been seeking to reduce the environmental impact of their operations, a process known as environmental upgrading (Navarrete et al., 2020), which could be achieved by increasing the use of bio-based feedstocks in their industrial processes (Bröring, Baum, et al., 2020).

But simply replacing industrial products from the fossil economy with bio-based products is not sustainable *per se*, and evidence about this is increasingly being discussed in the literature (Anlauf, 2023; Holz, 2023). In fact, at a large scale, it could mask further environmental degradation, especially (but not limited to) due to the use of first-generation feedstocks. Concerns over environmental sustainability have been raised for many products often associated with the bioeconomy, such as bioplastics (Escobar et al., 2018), biochemicals (Nong et al., 2020), biofuels (Jeswani et al., 2020) and bioenergy (Searchinger et al., 2022). Augmented demand for these first-generation technologies can lead to direct and indirect land-use change, increases in food prices, biodiversity loss, and other environmental side effects such as acidification and eutrophication. In this trajectory, a transition toward a bioeconomy will be without planetary boundaries and accelerate environmental degradation (Miranda et al., 2023).

Thus, embracing a purely substitutive approach based on the production and use of biomass entails several dangerous environmental side effects that may offset initial GHG mitigation promises (Broch et al., 2013; Searchinger et al., 2008) and create challenges for food security (Rulli et al., 2016). In the long term, for the bioeconomy to become a truly sustainable paradigm, we will need to shift away from biomass-intensive technologies toward more sustainable practices that require less biomass or use feedstocks that do not compete for food or land, such as low-value waste streams or higher-generation biomass sources (Escobar & Laibach, 2021; Stark et al., 2022). In this study, we characterize this evolution using the concept of bioeconomy upgrading, a long-term process that demands technological innovations and promotes changes in the use of biomass.

As depicted in **Figure *1.1***, the bioeconomy is characterized in its initial stages by attempts to substitute fossil-based inputs using first-generation technologies, often high-volume and low-value agricultural feedstock. However, advanced stages involve the use of higher-generation feedstocks, the adoption of circularity principles, and the design of new biosynthetic compounds. Eventually, a fully upgraded bioeconomy could simultaneously reduce the amount of biomass needed and rely on less land-intensive biomass, reducing the tradeoff between economic growth and environmental sustainability. As shown in **Figure *1.1***, this bioeconomy upgrading process entails two pillars of value creation: the **environmental dimension**, which relates to the minimization of environmental externalities by reducing biomass needs or adopting higher-generation biomass sources, and the **economic dimension**, which implies creating economic value added in low-volume and high-value trajectories.

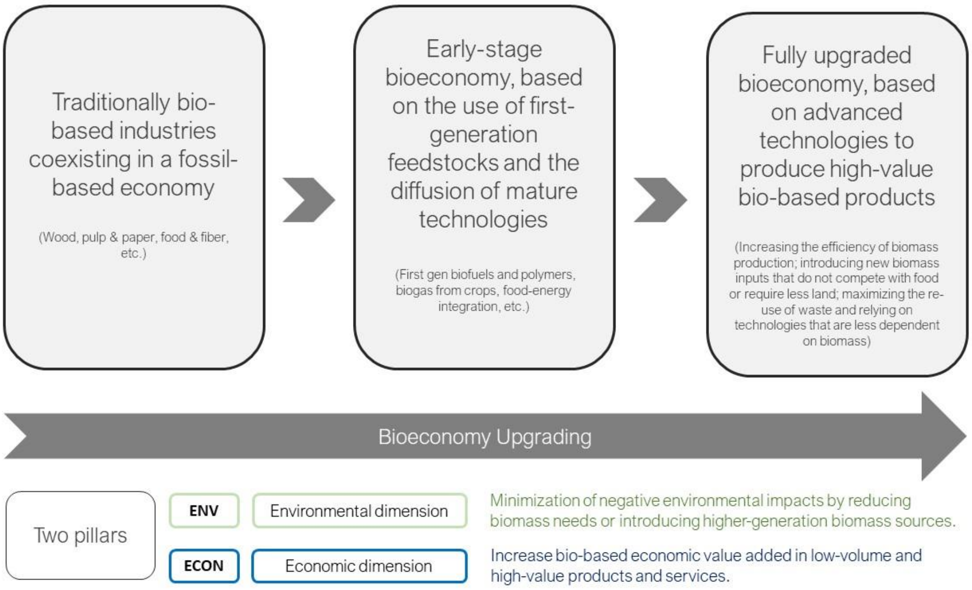

Figure 1.1. Stages in a bioeconomy upgrading. Environmental and Economic pillars.

Such a transformation can be reached through different paths that are not mutually exclusive: increasing the efficiency of biomass production (more output per unit of land or more value-added per ton of output), introducing new biomass inputs that do not compete with food or require less land to be produced (such as 2nd, 3rd, 4th generation feedstocks), maximizing the re-utilization of waste in multi-product biorefineries, and relying on technologies that are less dependent on biomass (i.e., high-value and low-volume applications) (Escobar & Laibach, 2021). A fully upgraded bioeconomy in which we have a decarbonized economic system that contributes to improved social equality will require a fast and large-scale adoption of these innovations to capitalize on the synergies and co-benefits (Hawken et al., 2017).

A sustainable bioeconomy requires a comprehensive technological transition in which radical innovations that are initially used in niche markets gradually become the new technical regime (Geels, 2002). This entails the emergence of a conducive business ecosystem that fosters the conversion of scientific knowledge into innovative applications. We already have examples of upgraded bioeconomy applications across several industries, such as biosimilars for human health, bio-inputs for agriculture, next generation of antibiotics and vaccines, new seed traits, animal-free recombinant proteins, bioplastics from waste, lignocellulosic biofuels, and algae applications (among many others).

1.3 Methodological approach

To answer the two research questions in this chapter, we follow a conceptual approach supported and illustrated by empirical, up-to-date business cases. This qualitative approximation is suitable for studying a nascent phenomenon such as the bioeconomy, for which historical data is limited (Glaser & Strauss, 1967; Yin, 2003). This methodological approach has been adopted by other authors addressing the study value chains in the context of innovation and learning, such as Bröring (2008), Pietrobelli and Rabellotti (2011), and Swinnen and Kuijpers (2019). Moreover, the field of agricultural economics has been successful in proposing quantitative approaches to study specific dyadic relations in a value chain (e.g., farmers-processing companies or processing companies-retailers), but approaching the study of complete value chains demands alternative methods (Bellemare, 2022; Macchiavello et al., 2022). In fact, recent papers that discuss structural transformations of entire value chains in the face of innovation adopt conceptual and qualitative approaches (Reardon et al., 2019; Sexton, 2013; Trienekens, 2011). In this line, our methodology follows a three-step path.

First, we start by doing a narrative review of the literature on the mutual dependency between value chain characteristics and processes of innovation, which we summarize in Section 1.4. Changes in physical technology often require adaptations within the value chain (e.g., new governance structures, changes in the industry structure, or the emergence and disappearance of firms). Still, at the same time, some value chain characteristics may create a suitable environment for the appearance of new technologies. We present literature explaining this twofold relationship between both categories (value chain features on the one side and characteristics of the innovation process on the other side) and extract some specific dimensions that characterize each of them. These dimensions will be used later to depict our value chain representative models.

Second, in Section 1.5, using insights from the literature on value chain management and industrial organization, we present six representations that describe the organization of value chains across the different stages of the process of bioeconomy upgrading. A value chain comprises a group of actors performing value-adding activities and several strategic interactions among them (Donovan et al., 2015). Each value chain has vertical boundaries (i.e., a start and an end) and horizontal boundaries (products, markets, and activities that belong to the value chain). However, there is no rule of thumb to set these limits, which depend on the research goals in each situation (Kaplinsky & Morris, 2001). Value chain mapping is a tool that helps to reduce complexity by depicting functions, actors, and their relationships in a simple and visually friendly way (Springer-Heinze, 2018).

We constrained ourselves to typify activities and their vertical links exclusively in the context of the bioeconomy. Assuming that the bioeconomy comprises the "*production, utilization, conservation, and regeneration of biological resources, including related knowledge, science, technology, and innovation, to provide sustainable solutions (…) within and across all economic sectors*" (International Advisory Council on Global Bioeconomy, 2020, p. 14), we map the following activities:

i. Biomass production (considering not only crops but also waste and other types of bio-based feedstocks).
ii. Bio-based processing (transformation of biomass into valuable bio-based products).
iii. Industrial applications (use of a bio-based product as an input for an existing industry).
iv. Biotech support or R&D services (development of novel technologies for bio-based processing or supporting activities for industrial companies).
v. Final consumption (representing final users, such as farmers, consumers of food products, medical patients, etc.).

By mapping activities rather than actors, we ensure that our value chain representations are as broad as possible. Functions tend to be more comprehensive and invariable, while the actors performing those functions may be case-specific and change according to different governance decisions. For the sake of simplicity, we excluded activities such as logistics, marketing, provision of other non-biobased inputs, financial services, and many others that should be included in a more detailed value chain mapping. We decided to keep the final users in the conceptual models because this helps to understand the orientation of the value chain and also contributes to our subsequent discussion about welfare effects. These value chain representative models are illustrated with real business examples from the current bioeconomy landscape.

Lastly, in our third methodological step (in Section 1.6), we discuss how the changing characteristics of these value chains in the context of a bioeconomy upgrading might affect income distribution for the participants. Since many bioeconomy innovations are not yet at a market stage, there is hardly any empirical evidence available on their welfare distribution effects. However, based on the available literature on value chains, we can hypothesize several social sustainability implications of changes in the value chain dimension. The narrative of the bioeconomy has been built upon sustainability aspects, usually with an emphasis on the environmental dimension (Boyer et al., 2023). However, discussions from a social perspective have been largely absent, so it is unclear how the bioeconomy may contribute to goals related to the quality of life of the actors involved (Lühmann & Vogelpohl, 2023; Martinelli et al., 2022). Even though it is a hypothetical exercise, the contribution of this analysis is to propose ideas for further research and accentuate, in a context in which many governments are presenting or updating their bioeconomy strategies, that social sustainability aspects cannot be absent in the discussion.

1.4 The nexus between value chains and innovation

The literature on the drivers of technological innovation and value chain formation suggests that there is codetermination between the organizational structure of value chains and the type of technological innovation adopted inside the value chain. On the one hand, the rise of a new technology in an industry may affect the characteristics of its value chains, as managers might need to change how their businesses are organized to incorporate new processes or inputs. On the other hand, some value chain features are inherently more conducive to fostering an endogenous innovation process. We explore each direction of the relationship in more detail in this section.

a. *New technologies contribute to shaping value chains.*

The emergence of a new technology in an industry might lead to a reorganization of its associated value chains. This happens mainly for three reasons. First, innovators face several risks when dealing with new technologies. Whether these innovations were driven by government regulations, consumer preferences, or entrepreneurial initiatives, risks exist both from the supply side (i.e., final output, quality of feedstocks) and the demand side (i.e., commercial failure). Thus, companies might look for alternatives to organize their value chains to reduce and control part of these risks. Upstream, this affects the decision to produce feedstocks in-house or acquire them through contracts or market mechanisms (Du et al., 2016). Downstream, this affects how distribution channels and marketing activities are handled. Likewise, many innovations show specificities that create hold-up opportunism. In this case, the proper contractual schemes must be designed for successful technology transfer (Kuijpers & Swinnen, 2016; Swinnen & Kuijpers, 2019).

Second, many novel technologies show increasing returns of scale. This means substantial investments are needed in the development phase, but marginal costs are low when the technology scales up and becomes viable (Zilberman et al., 2012). This takes particular relevance in the presence of market failures since entrepreneurs may have limited access to funds (Zilberman et al., 2019). In such a context, companies need to develop partnerships with R&D firms or associate with similar companies to scale up and facilitate investments. In the long run, these increasing returns of scale may result in value chains comprised of firms of bigger size, which are the ones that can overcome credit and scale barriers.

Third, many innovations are intrinsically systemic. This means that different value chain members must adapt for the technology to succeed. In this case, companies may choose governance structures that give them more control over production and commercialization (Bröring, 2008). Moreover, systemic innovations often require platform leaders who promote collaboration along the value chain (Gawer & Cusumano, 2014; von Pechmann et al., 2015). A recent example can be seen in the widespread adoption of e-commerce solutions during the coronavirus disease (COVID-19) pandemic, where we observed, for example, firms in the food industry, their suppliers, and intermediaries change their operations to adapt to make efficient use of these new technologies (Reardon, Heiman, et al., 2021).

b. The morphology of value chains affects the rate of innovation.

The organizational structure of value chains can influence technology transfer and how likely technological innovation will be fostered endogenously. First, the prevailing governance schemes shape the learning and knowledge-sharing mechanisms along the value chain: while in arm's-length arrangements learning happens mostly through knowledge spillovers or imitation, in contract-intensive value chains, more structured learning mechanisms prevail, such manuals of procedures, production standards, or in-person training (Pietrobelli & Rabellotti, 2011). Value chains with poor contract enforceability may affect technology transfer and require specific safeguards (Kuijpers & Swinnen, 2016).

Second, the predominant market structure in the value chain affects the scope and speed at which innovation occurs. Market leaders can create demand for novel products and engage many upstream and downstream value chain actors. Hence, value chains comprised of leader firms with strong innovative capabilities or a tradition of innovation are more likely to produce further innovations. Horbach (2008) finds that a firm's technological capabilities affect its environmental innovation level. Mazzucato and Robinson (2018) describe the key role that NASA has played in promoting innovations among private-sector contractors in the aerospace industry, many of which had spillovers toward other industries. In a similar line, Allal-Chérif et al. (2022) study how a leading firm in the aeronautics industry, like Airbus, is collaborating with suppliers to develop innovations that reduce the carbon footprint of its operations. However, it is also possible that companies with considerable market power can control the speed and scope of technical change and hinder the scaling of certain technologies (Clapp, 2021b).

Third, value chains that operate in collaborative environments, not only among firms but also between the private sector and research institutions, are more likely to foster innovation, especially in the environmental field for which private incentives are weak (Bossle et al., 2016). The role of collaboration is evident in knowledge-intensive industries where proximity among firms fosters open innovation, like in pharma (Demirel & Mazzucato, 2010) or biotechnology (Casper, 2007; Segers, 2015).

Overall, we conclude from the literature that there is codetermination between the innovation process (i.e., intensity and main characteristics) and the structure and morphology of a value chain. This codetermination implies that the value chain structure is endogenous to the type of innovations and the technologies adopted, but at the same time, different value chain features may help to foster innovations.

A synthesis of the literature discussed in this section is shown in **Table *1.1***. There, we summarize three specific dimensions to portray each of our two categories of analysis (A. characteristics of the innovation process and B. value chain features). To characterize the innovation process, we synthesize three dimensions from subsection 1.4.a: the level of risks entailed by the technology (A.1), the level of investments and capital required by the technology (A.2), and the systemic characteristics (A.3). To depict value chain features, we also present three dimensions coming from the literature presented in subsection 1.4.b: the type of governance in the value chain (B.1), the predominant industry structure throughout the value chain (B.2) and the level of collaboration and open innovation practices among value chain participants (B.3).

In the next section, we will present a comprehensive typology of bioeconomy value chains and use these dimensions from **Table *1.1*** as the base to describe and characterize these models.

Table 1.1. Main categories of analysis.

Category	Dimension	Definition
A. Characteristics of the innovation process	A.1 Technological risks	Degree of novelty in the technology. Degree of specificity. Potential hold-up risks. Need to develop markets. Need to protect intellectual property (IP).
	A.2 Level of investments required	The magnitude of the initial investments required to develop new technology. Potential increasing returns of scale. Sunk costs.
	A.3 Systemic characteristics	Level of adaptations needed by different members of the value chain to implement a technology. Platform characteristics and potential network externalities.
B. Value chain features	B.1 Value chain governance	Ways of interaction among value chain members (market, contracts, hierarchy)—rule-setting mechanisms.
	B.2 Predominant industry structure	Size and number of firms. Level of sales and market shares. Presence of leading firms that promote innovation and engage other value chain members. Length of the value chain (number of stages end-to-end).
	B.3 Collaboration and Open Innovation	Alliances and partnerships among firms. Knowledge sharing. Convergence and inter-industry collaboration. Strategic alliances and joint ventures.

1.5 Typology of value chains in the bioeconomy

a. Value chain conceptual models

To answer our first research question, we present six value chain maps that typify activities and their vertical links in the bioeconomy in **Figure *1.2***. We relate these value chain models to specific technological innovations and empirical examples from consolidated and emerging companies. We briefly describe these models in the remainder of this section, based on the categories presented in **Table *1.1*** (A1-3 and B1-3) and the two pillars of a bioeconomy upgrading described in **Figure *1.1*** (ENV and ECON).

Model 1: low-value, high-volume biomass

This first model represents the earliest developments in the bioeconomy, in which bio-processing companies procure feedstocks from biomass producers through market mechanisms, and the bio-based product then becomes the input of an industrial process. This structure is common in first-generation biofuels or biogas from edible crops. The Argentine oilseeds crushing industry can be cited as an example. The country has one of the biggest soybean crushing clusters in the world, and after the biofuels law was passed in 2006, many companies built plants to convert soybean oil into biodiesel (Calzada & Molina, 2017). Crushers buy soybeans through market mechanisms and then sell the biodiesel to refineries that blend it with oil. A similar value chain structure is observed in other first-generation biofuel value chains (ethanol and biodiesel), such as Brazil, Colombia, and Guatemala (Canabarro et al., 2023). Another example of this type of structure is the palm oil value chain in Southeast Asian countries like Indonesia, Malaysia, and Thailand, in which plantation is performed by a wide range of suppliers of different sizes, generally in geographical proximity to processing companies (di Canossa, 2020). Due to the need for costly infrastructure, the refining and processing activities are done by a small group of large companies that normally source palm feedstocks from both their own and third parties independent plantations (Pacheco et al., 2017).

While processing companies are always looking for new uses for their by-products (e.g., crude glycerine in the case of biodiesel), the main processing technologies are mature and involve low technical risks. Thus, innovation intensity is low in this value chain model. Investments in fixed assets, technical efficiency, and logistics are key success factors, and no systemic adaptations are involved. For these reasons, feedstock procurement often happens in arm's length transactions governed by market mechanisms. Some companies might prefer to secure contracts with their suppliers, but these are not strictly necessary given the non-specificity of feedstocks. In addition, firms have few incentives to collaborate and develop new technologies because these industries rely on mature technologies.

Currently, this type of value chain represents industrial processes characterized as low-value and high-volume, mainly aimed at the substitution of fossil-based products. There are potential GHG emissions savings, but there are also risks of land-use change that can create further environmental impacts such as biodiversity loss, eutrophication, or acidification. In the long run, these side effects can outperform gains from reduced emissions (Jeswani et al., 2020; Stark et al., 2022).

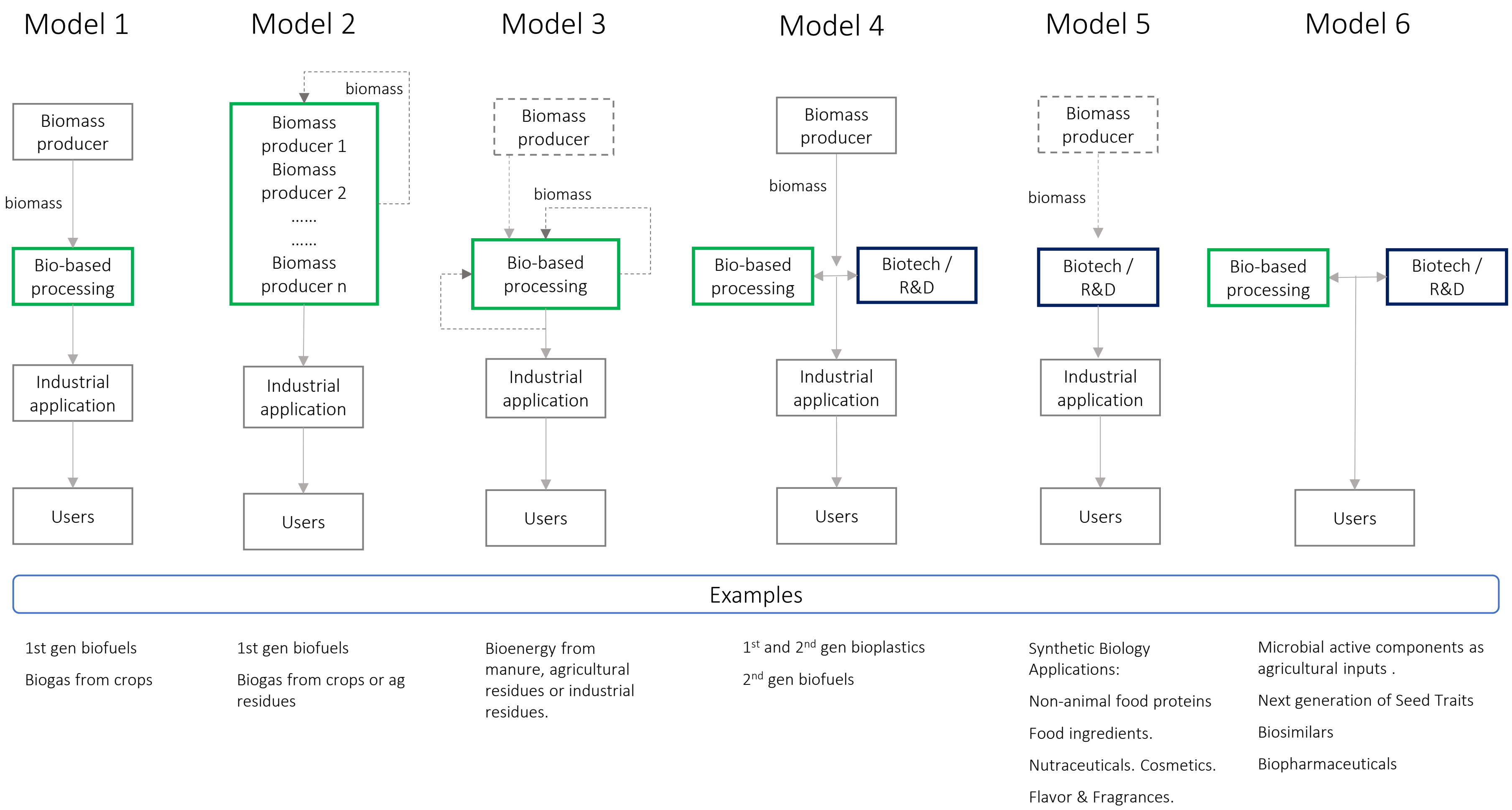

Figure 1.2. Typology of value chains in the bioeconomy.

Models 2-3: adoption of cascading and circular principles

The next two models are closely linked, as they introduce some degree of vertical integration and horizontal cooperation in the bioeconomy[1]. In the second model, biomass production and bio-based processing are integrated. It is usually biomass producers (i.e., farmers) who forward integrate towards the bio-based processing stage, seeking to increase the value-added of their output. This is done mainly through local biorefineries, which can later incorporate additional processes and cascading uses. The emergence of cooperatives in the U.S. corn ethanol industry works as an example. Despite transaction costs, Midwest farmers organized themselves in cooperatives after the 1978 Energy Tax Act, mainly in response to the absence of local corporate buyers. This also happened even in the presence of private corporations in counties with a tradition of cooperative culture (Boone & Özcan, 2014). Model 2 also depicts a type of organization that has become common in many European countries: small farmers' associations for converting manure or crop residues from their farming operations into biogas via anaerobic digestion, obtaining biofertilizer as a by-product (Scarlat et al., 2018). Another example of this value chain representation is social innovation initiatives in developing countries involving local small farmers´ networks to cooperate in valorizing agricultural waste (typically through bioenergy), such as the case of rice producers in Asia (Minas et al., 2020).

In the third model, an agro-industrial company (or maybe a large-scale farm) installs a biorefinery to add new cascading uses to its biomass. This is a typical structure in the production of biogas and bioenergy from industrial waste, crop residues, or animal manure (FAO, 2020a). Residual biomass employed in model 3 is bulky and has low or no market value. Thus, these new bio-based processes should be carried out in local biorefineries, which can be supplied entirely from the company's own feedstocks or may require external sourcing to reach a minimum operative level. The company can choose the optimum mix of in-house use and external sale of the bioenergy generated. As specific examples, we can mention dairy farms using cow manure for anaerobic digestion in Italy (Vida & Tedesco, 2017), farmers joining forces to use residues from hog production in Denmark (Skovsgaard & Jensen, 2018), or forest product companies adding value to wood chips and other dry residues in Finland (Näyhä, 2019). We can also identify several cases of food companies using residues to produce bioenergy from fruit peels (Raimondo et al., 2018), potato residues (Klein et al., 2022), peanut shells (Streetz, 2021), olive tree prunings (Palmieri et al., 2020), and cocoa waste (Njeru, 2021). The production of electricity from bagasse, a usual practice among sugarcane mills in Brazil, also fits into this value chain model (Chaddad, 2010).

Since these are biomass-intensive models and transport costs might be prohibitive, in-place processing and geographical coordination are crucial for success. The technologies involved, such as biodigesters or distilling facilities, are mature and can even be bought as turnkey solutions, entailing a low level of systemic adaptations. The bioeconomy at this stage is more about the diffusion of known technologies rather than the development of new ones.

The main challenges in these two models come from organizational rather than technological aspects, in which business models need to be adapted to embrace circular practices (Donner & de Vries, 2021; Santa-Maria et al., 2022). Both vertical integration and horizontal cooperation pose additional management challenges for the ones involved, so some local actors need to take

[1] Dotted boxes and arrows in Figure 1.2. reflect the fact that biomass flows might not come from market transactions but take place within a hierarchical or coordinated governance structure.

the lead to promote and coordinate these initiatives. Some specific forms of governance, such as collection agreements, might be required in the case of waste.

The main economic value added in models 2 and 3 is still related to the substitution of fossil-based products (i.e., biofuels, biogas, electricity, and biofertilizers are all examples of possible outputs in these models). However, those ventures in models 2 and 3 that rely on the circular use of waste are in a better place for mitigating the environmental externalities posed by the use of first-generation feedstocks. In the long run, this requires what Bröring et al. (2020) define as behavioral innovation in the bioeconomy. The emergence of small-scale biorefineries may also create new jobs and motorize economic activity at a local level.

Model 4: Higher-generation feedstocks and advanced technologies

This model has a similar structure to model 1, but we see an additional function: R&D and biotech support. Using higher-generation feedstocks and getting advanced products from first-generation biomass require more complex processing techniques. These are not turnkey technology platforms, so the company in charge of biomass processing often works closely with a high-skilled technological partner.

The first example of this value chain model comes from the bioplastics industry, in which chemical or petrochemical companies associate with biotech companies. For example, the petrochemical company Total joined forces with the biotech company Corbion to produce polylactic acid (PLA) polymer resins from sugarcane (Kees, 2017) and with the Chinese synthetic biology company Bluepha to develop high-performance biopolymers and foster market access in Asia (Laird, 2023). We can also mention the company Synvina, originally developed as a joint venture between Avantium – a technology company that develops chemicals based on renewable resources – and the chemicals company BASF to produce bio-based furandicarboxylic acid (FDCA), which can be used for the production of green chemicals[2] (de Jong, 2018).

This value chain structure is also typical in industries that rely on second-generation technologies. For instance, Poet (an ethanol company) and Royal DSM (a science-based company) created a joint venture to produce cellulosic bioethanol in Iowa. A comparable experience occurred in Italy with a cellulosic ethanol plant in Cresecentino, originally coming from a partnership between the chemical Mossi & Ghisolfi and the industrial enzyme leader Novozymes[3] (Wydra, 2019). Similarly, Avantium promoted a consortium, including many other industrial partners, to build a pilot biorefinery in Delfizjl to produce sugars and lignin from woodchips (Vels, 2021). In Brazil, two second-generation ethanol plants use sugarcane bagasse and straw as primary inputs. One is an association between GranBio and Beta Renewables, and the other is a joint project between Raízen and Iogen Energy in cooperation with Novozymes (Neto et al., 2018). Recently, the consumer goods company Unilever signed an agreement with the U.S. biotech company Genomatica to produce plant-based and waste-based alternatives for palm oil, one of their critical feedstocks for personal care products (Bettenhausen, 2022).

However, it is important to note in the case of advanced biofuels that the growth in this sector would be contingent upon significant cost reductions to ensure competition with fossil fuels. As such, the transition towards an upgraded bioeconomy might be especially challenging in sectors

[2] In 2019 Avantium acquired all of BASF’s shares.
[3] The plant now belongs to Versalis (subsidiary of Eni group).

such as aviation, shipping, and long-distance trucking, which are responsible for around 20% of all GHG emissions from global food systems (Li et al., 2022).

Unlike models 1 to 3, investments in fixed assets are not enough: funds for R&D are also needed. This may be expensive (especially in the early stages) and necessarily implies a learning curve. This model is close to what Biber-Freudenberger et al. (2020) define as the manufacturing sector in the bioeconomy (high-volume biomass sector). Companies need to profit from economies of scope in multi-product biorefineries to make the business economically viable.

Given that the specificity of feedstocks increases, upstream systemic adaptations are needed, and thus contracts may be preferable. Contracting allows the bio-processing company to secure feedstock procurement while guaranteeing the farmers a selling channel for a highly specific output. Since 2nd, 3rd, and 4th generation feedstocks may have few alternative uses in a particular region, some monopsony power may be created. Collaboration between technology developers and industrial clients seems to be a core task in this model.

In model 4, the use of biomass is still intensive, but the value-added is higher compared to models 1-3. This model also seeks to depict the adoption of more sophisticated feedstocks which require less arable land or do not compete with food, so there is a higher potential to mitigate environmental externalities.

Model 5: low-volume, high-value biomass

Synthetic biology, one of the workhorses of an upgraded bioeconomy, uses genomic techniques to develop new synthetic compounds that are currently sourced from Nature (Brooks & Alper, 2021). Model 5 represents a value chain structure that reflects what might be happening soon in the field of synthetic biology. The promise behind these ventures is twofold. First, new synthetic compounds can replace substances that are either rare and very hard to obtain or whose extraction creates undesirable environmental impacts (e.g., synthetic nootkatone, used as an insect repellent, or synthetic artemisinin, used for malaria treatment). Second, synthetic biology can (partially) replace animal proteins, therefore reducing land needs, mitigating GHG emissions from land use change, and improving animal welfare (Lv et al., 2021). Here, a highly-skilled biotech company applies genome editing to engineer new living cells, and biomass is used as a base for fermentation. The synthetic compounds obtained from these processes become the input of existing industries.

The most common applications in this field are nutraceuticals, flavor and fragrances, and cosmetics (Wydra, 2019). Many companies are using synthetic biology to produce ingredients based on engineered yeast (Voigt, 2020). In the last five years, we have seen the rise of many startups in the non-animal food ingredients industry. For instance, The Good Food Institute (2021) reports more than 50 companies developing alternative proteins, such as animal-free eggs (Clara Foods), meat (Motif), or milk whey (Perfect Day), to mention a few. While most of these companies are based in the US and Europe, we are also seeing startups emerge in other regions, such as South America (e.g., NotCo, Future Cow, Michroma), Asia (e.g., Shiok Meats, IntegriCulture, Spiber) or Africa (e.g., Mogale, Mzansi Meat). While some products in this field have already reached a commercial scale (mainly pharma and cosmetics), others are still working on a low-scale or pilot phase (especially those related to food substitutes).

Some of these technologies require edible feedstocks (sugar or starch), while many other projects base their applications on second-generation biomass (residues or non-edible feedstocks). Moreover, fermentation not only occurs through biomass but is also based on microbial hosts, a process defined as precision fermentation (The Good Food Institute, 2021). In any case, the precision techniques used increase fermentation efficiency per unit of biomass (Augustin et al., 2023; Teng et al., 2021), so we may see a decrease in biomass-use intensity compared to the previous four models[4]. Moreover, the potential replacement of animal-based protein and other food ingredients with synthetic alternatives may reduce pressure on land use, considering how intensive the requirements of food systems are for production space (Alexander et al., 2015). From an economic standpoint, this value chain model can be considered a low-volume and high-value transformation pathway (Dietz et al., 2018). This implies bringing new products and biochemical processes to the market, most of which do not exist in the fossil-based economy.

Risks of failure associated with the innovation process are considerable since the techniques applied by the companies in this model are tailor-made and imply a continuous interaction between scientists and entrepreneurs. There are systemic characteristics, and collaboration needs that become evident in the stage of product development.

Firms need to control the value chain, both upstream and downstream. Upstream, it is unlikely that biomass used in a fermentation process will be sourced through pure market mechanisms since the control over its quality needs to be strict. Downstream, developing selling channels for synthetic products is challenging and often requires commercial partnerships with established companies. Currently, many startups are deploying synthetic biology applications. Still, in the long run, increasing returns of scale might require the presence of companies with a size that allows them to undertake the level of investments needed. Small science-based ventures can develop the initial stages of a specific technology and then sell it or associate with industry leaders to scale it up.

Model 6: biomass-free biotechnologies

Different bioeconomy definitions often highlight the combination of biomass and biotechnology. However, there are products and services in the bioeconomy almost exclusively based on biotechnology research and do not necessarily involve biomass flow. Model 6 depicts these types of initiatives. In this value chain structure, there is no bio-based processing as such, but rather a convergence of companies that hold specific industry knowledge with companies that provide biotechnological research platforms. This convergence can take many forms, from completely structured joint ventures to more informal partnerships or alliances. Moreover, the cross-industry merger and acquisitions rate is also an indicator of complementarities in the bioeconomy (Rennings et al., 2022; Waßenhoven et al., 2021).

We can mention a few examples to illustrate this model. A first example is the development of active microbial bio-inputs for the agricultural sector, for which traditional agricultural input companies are associating with biotech companies (e.g., Syngenta-AgBiome, Bayer-Gingko Bioworks, De Sangosse-Kan Biosys, Helm Argentina-Protergium). A second example comes from the healthcare industry, in which we observe partnerships between pharmaceuticals and biotech companies to develop biosimilars (e.g., Amgen-Allegran Kanjinti and Mylan-Biocon

[4] Alternatively, we could hypothesize that, as fermentation efficiency increases, prices could drastically decrease, thus greatly increasing demand. Such rebound effect could further increase biomass flows and pressure on land.

Ogivri, both Herceptin biosimilars) and a new generation of pharmaceuticals relying on biological principles (e.g., Gingko Bioworks-Roche for the development of advanced antibiotics). Finally, the joint initiatives between Cellscript-Moderna and Pfizer-BioNtech for developing genetic-engineering-based COVID-19 vaccines is another example of this model (Gaviria & Kilic, 2021). As we can see from these examples, we have complementary companies joining forces to bring new low-bulk and high-value applications to the market. Many of these ventures are focused on microbial platforms, metabolic engineering, and genome editing, which are among the leading enabling technologies for the future of the bioeconomy (Laibach et al., 2019).

As previously described, many platforms are not strictly based on biomass processing. Thus, in this case, the risk of environmental impacts seems low. However, caution is necessary. As in model 5, the reliance on new genetic techniques and the application of engineering principles to life sciences might also bring some concerns regarding potential biosecurity hazards to human health and biodiversity and require regulation (Macfarlane et al., 2022; Reynolds, 2021).

As in model 5, companies face a high risk of failure in the product development stage. Regulation is an issue, especially in human health products. The need for managing and protecting IP leads companies to gain more control of their value chain by getting involved in different stages. Since it is unlikely that one individual company can hold the complete set of skills needed for this type of complex process, inter-industrial collaboration, platform sharing, and research interaction are unavoidable.

b. The relation between the six value chain models and the concept of bioeconomy upgrading

Figure *1.3* summarizes how each value chain model relates to the process of bioeconomy upgrading, both in terms of the economic value added and the potential to reduce adverse environmental effects (as defined in Section 1.2). All of these types of bio-based value chains hold the potential to contribute to environmental sustainability and create business opportunities. However, the last models seem to have fewer risks of undesired environmental externalities because they are either based on more space-efficient feedstocks and waste or rely less on biomass. From an economic perspective, products and services in the last models present higher value-added and are closer to final users (we move from biofuels, bioenergy, or biofertilizers to biopharmaceuticals, biocosmetics, and food products, to mention a few examples). In **Appendix 1** ***1***, we present a table with more details expressing how each model is linked to a process of bioeconomy upgrading.

In Section 1.4, we discussed the codetermination between two overarching categories, value chain features and the characteristics of the innovation process, and presented three main dimensions (A1-3 and B1-3) depicting each of them. This is the underlying concept behind our first research question, which asked which value chain features may be more conducive to a process of bioeconomy upgrading. Our six value chain representative models show that, on the one hand, we will likely observe changes in the morphology of value chains as the biotechnology intensity increases. On the other hand, some value chains show features that could be more favorable to innovation and accelerate the rate at which new technologies are developed and adopted. This is summarized in **Figure *1.3***, where we briefly characterize each value chain model in terms of the dimensions A1-3 and B1-3.

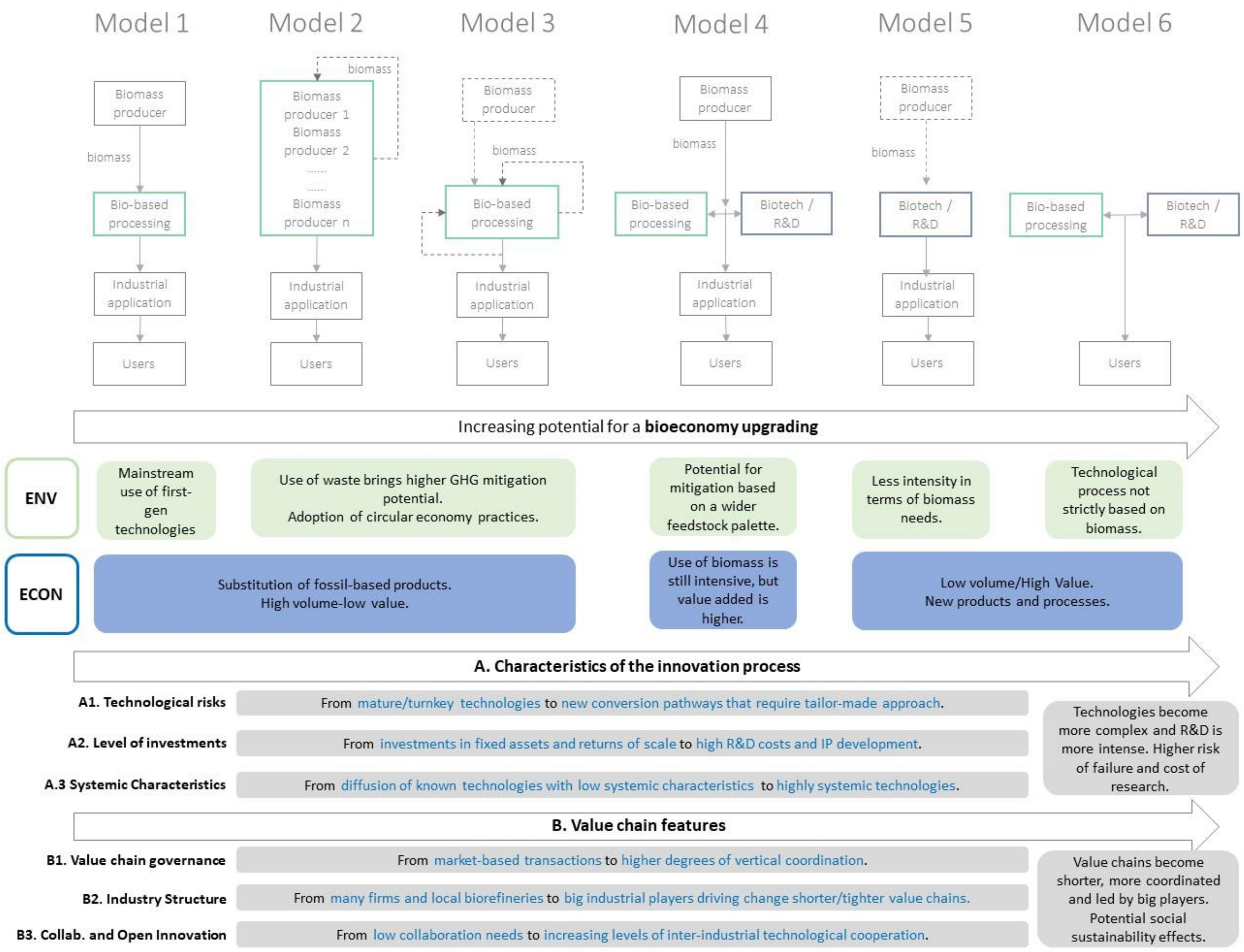

Figure 1.3. Bioeconomy value chain typology and the bioeconomy upgrading.

Regarding the **characteristics of the innovation process** (dimensions A1-3), each of our bioeconomy value chain representations involves different levels of scientific research and biotechnology skills (summarized in **Figure *1.3***). In Schumpeterian terms, models 1 to 3 are characterized by the diffusion of mature and turnkey technologies, while models 4 to 6 rely on the transition from invention to innovation, in which either new technologies are developed or known technologies are used to create new bio-based products. At the same time, models 1 to 3 and partially model 4 rely critically on biomass availability, for which logistics and handling efficiency are key to success. Models 5-6, on the other hand, belong to a low-volume and high-value transformation pathway in which biomass handling is not essentially a success factor. Thus, when we go from left to right in **Figure *1.3***, the rate of innovation intensifies (both in products and processes). Hence, risks and uncertainties increase, higher capital requirements are needed, and systemic characteristics and network effects become more evident. **Appendix 1 *2*** presents an extended analysis for the categories A1-3 in the six value chain representative models.

In terms of **value chain features** (dimensions B1-3), these also change when we move from left to right in **Figure *1.3***. Companies working in structures like in Model 1 can rely on market mechanisms to source biomass, considering the low specificity of the feedstocks involved. The organizational structure of Models 2-3 introduces the need for some contracting schemes (i.e., collection agreements in the case of waste or contracts in the case of horizontal alliances of farmers). This is more evident in models 4-5, where the higher specificity of the biomass involved leads to more detailed contracting schemes, which is done to provide market safeguards for biomass producers because higher-generation feedstocks have few alternative uses or because feedstocks involved in precision fermentation need better quality and traceability. Moreover, the increasing complexity of the research process and the technologies involved demands more cooperation and open innovation activities among research firms. In models 4-6, there is an interaction between the innovation supply chain, which develops the technical knowledge for new products or services, and the product supply chain, which is in charge of reaching the market (Zilberman et al., 2022). In this group of models, the multiple research and market risks involved and the high capital requirements bring to the fore the role of prominent industry players in bringing new technologies to market. **Appendix 1 *3*** extends the analysis for dimensions B1-3 in the six value chain models.

We acknowledge that the models presented reflect a more static than dynamic approach. The concept of technological trajectories implies that models 4-6 might probably replicate some of the characteristics of models 1-3 in the future when technologies mature and become more accessible. As low-impact technologies evolve and biomass gets "commodified" in the future (e.g., algae or switchgrass technologies), we might observe value chains getting closer to the organizational structures that we currently associate with low-value and high-volume mature technologies, such as first-generation biofuels. Moreover, the models presented in the typology should not be understood as separate compartments without interlinkages. Part of the more advanced products of the bioeconomy are supposed to supply more traditional value chains in the future. For example, agricultural bio-inputs or second-generation seed traits reflected in Model 6 will likely provide inputs for biomass production for all the models.

1.6 The social sustainability dimension of a bioeconomy upgrading

The value chain features associated with each of the models in a bioeconomy upgrading are nontrivial from the social perspective. While innovation is crucial to safeguard environmental sustainability in the bioeconomy (or at least minimizing environmental impacts), social sustainability aspects should not be thrust aside, given that costs and benefits from an intensified rate of innovation may be redistributed among value chain actors. Defining the scope of social sustainability is challenging and disputable (Desiderio et al., 2022), but for the purpose of this paper, we understand social sustainability as related to the inclusion of smaller value chain actors and the overall well-being and life quality of individuals and households. This comprises several aspects, such as income levels, job availability, equitable income distribution, and accessibility to technology and final goods.

The distribution of the value-added created in a bioeconomy upgrading poses many questions. For example, the cost of new bio-based products may be prohibitive to some consumers (Timmermann, 2020). Will every consumer have access to these new bio-based products at a reasonable price? In the case of farmers, they might have to bear extra costs to comply with additional value chain requirements (Ponte, 2020). But are small farmers going to be able to participate in upgraded value chains and get a fair share of the new market opportunities? And what about midstream actors? They partially contribute to the creation and diffusion of innovations (Reardon, 2015), but to what extent this will happen in new bio-based value chains is unclear.

Another set of debates relates to how roles in bioeconomy value chains will be distributed among Global North and Global South economies. Our six value chain representative models may evolve at a different speed depending on the economic development of a country or region. Models 1-3, which are rather biomass-intensive, may likely multiply in developing and transition economies that are more dependent on agricultural resources (Biber-Freudenberger et al., 2018) and have extensive land availability and biodiversity richness (FAO, 2021; Kass et al., 2022). On the contrary, we may see a faster evolution of models 5-6 (and partially 4) in developed nations, with a longer tradition of biotechnology research and more dense networks of research institutes and universities. This can be confirmed by looking at bioeconomy strategies, in which high-income economies include more frequently high-value and low-volume pathways than low-income economies (Dietz et al., 2018). Thus, a bioeconomy upgrading could reinforce global inequalities with an extractive logic by restricting the Global South to the role of biomass providers, whereas high-value activities remain in the Global North (Eversberg, Koch, et al., 2023).

We use each of the value chain features presented in **Table *1.1*** (B1-3) to discuss how the expected transformation of value chains in the face of a bioeconomy upgrading might affect the income of the participants and create effects on the well-being of people and households.

a. Social sustainability implications of changes in governance schemes

In section 1.5, we claimed that augmented bioeconomy innovation is associated with shorter and vertically coordinated value chains. Value chains become tighter when specific research activities are required. There are two main reasons behind this. First, markets for some bio-based products are not yet developed. Downstream, innovators need to develop distribution channels and deal with consumer acceptance. Upstream, higher-generation feedstocks (e.g., energy crops, algae, lignocellulosic waste) tend to be transaction-specific, so innovators need to offer farmers a secure selling channel, usually done through contracts. Even collection agreements may be needed for residual biomass. The second reason is related to the systemic nature of innovations in the bioeconomy, which compels firms to engage in many value chain steps to improve control. The need to protect IP rights while transferring technology demands more vertical integration (P. Lee, 2018). This holds especially in contexts lacking strong institutions that safeguard IPRs. However, where such institutions exist and are well-functioning, firms might be more willing to use licensing (Deconinck, 2020).

In this context, the first question is related to the inclusion of small farmers in upgraded bioeconomy value chains. Previous experiences show that while different forms of inclusion are possible (Maertens & Swinnen, 2009), there are also risks of exclusion when small and large farms coexist (Reardon et al., 2009). Smaller farms probably lack the scale, capital requirements, and non-land assets to supply big processing companies. This may favor contracts with larger farms to secure feedstock procurement.

Another discussion is related to potential costs created by new environmental compliance requirements. These additional costs could be pushed upstream to farmers (Ponte, 2020). Also, smallholders might be forced to make upgrading investments if they want to keep selling, as has happened with private standards in the past (J. Lee et al., 2012).

Finally, the effects of vertical coordination on farmers' well-being are still under debate. Despite contracts being considered a way to improve farmers' livelihoods, these benefits are context and product-specific (Meemken & Bellemare, 2020; Ruml & Qaim, 2020). Many of the studies in this field lack external (and, in some cases, internal) validity (Bellemare & Bloem, 2018). Thus, it is better to be cautious rather than conclusive on this issue.

b. Social sustainability implications of changes in predominant industry structures

An acceleration in bio-based innovation could potentially increase market shares and concentration since moving from first-generation to advanced feedstocks requires expensive investments in R&D. And these investments are not always a clear shot: risks of failure bring sunk costs into the cost equation. Additionally, biological organisms are not completely controllable, so there is a steep learning curve and periods of trial and error. Thus, bigger companies are in a better position to deal with all these issues, at least until these technologies are mature and more accessible. Likewise, industry leaders can become key facilitators of a bioeconomy upgrading by setting supply chain standards while simultaneously helping to create downstream markets. This is especially relevant in models 4 to 6 since, in models 1 to 3, it is easier for smaller actors to get involved.

There is mixed evidence of distributional effects from the augmented buyer and seller market power in agricultural value chains (Swinnen & Vandeplas, 2010). However, in the case of the bioeconomy, we can expect big players from buyer-driven value chains to take the lead, especially in consumer-oriented applications (i.e., cosmetics, nutraceuticals, food). This has implications for the international division of labor: if developed countries are the ones who own the patents and focus on R&D and downstream activities, then developing countries will be constrained only to the supply of raw materials (Börner et al., 2017; Puder & Tittor, 2023), so the additional benefits from bioeconomy innovation will likely stay in developed countries. However, benefit sharing will ultimately depend on the type of technology being discussed: research has suggested that farmers have reaped most benefits from GM soybeans in the USA and not the seed companies (Ciliberto et al., 2019).

There are two immediate concerns about market power: prices and investments in R&D. The effect is not evident in the case of prices. For instance, while the increased concentration in low R&D industries, such as the fertilizer industry, has raised input prices, the overall effect on prices from concentration in the seed and biotech industries is still disputed (Deconinck, 2020). Evidence is divided for R&D investments as well. The belief is that higher market shares allow firms to allocate money for risky ventures. But while some authors support this (Chassagnon & Haned, 2015; Smolny, 2003), others state that the effects of concentration on innovation are unclear (del Río et al., 2016) or even negative (Béné, 2022; Clapp, 2021b). Nonetheless, it is important to note that despite the growing role of private R&D in developing technologies for the agri-food sector, public investments are still relevant and often complementary to private R&D (Pray & Fuglie, 2015).

A final effect related to low-volume and high-value trajectories is how the possibility of creating food substitutes in a lab will affect the income of cattle and dairy farmers – albeit reducing negative environmental externalities. The final effect will depend on whether new synthetic products work as complements rather than substitutes to traditional value chains and the role of industry leaders in adopting and promoting those new products (Howard, 2022).

c. Social sustainability implications of increased collaboration among firms

In the long run, a bioeconomy upgrading calls for open innovation trajectories based on collaboration and cooperation among companies in value chains. This can take many forms, such as alliances, partnerships, joint ventures, or mergers and acquisitions. As we saw in section 1.4, moving from turnkey to tailor-made technologies (models 4-6) naturally leads to sharing knowledge since one single firm cannot have all the skills required and need to rely on capacities developed by others.

An accelerated rate of innovation in the bioeconomy increases the relative weight of biotechnology compared to biomass. This opens a gap for startups and small tech firms to assume risks by becoming early-stage developers of new technologies (Tsvetanova et al., 2021) and then scaling up in association with other firms. Inter-organizational collaboration is crucial to foster innovation among SMEs (Baum et al., 2000), and developing countries can promote new hi-tech startups and support the creation of local innovation ecosystems. Furthermore, these SMEs can benefit smallholders, even in a non-contract environment, by transferring knowledge and technology to them (Liverpool-Tasie et al., 2020).

But are small firms going to be able to survive? Or will big firms end up taking them over? While small startups can be the first movers, research funds and scale become crucial for survival in the long run (P. Lee, 2019). When small firms run out of funds, the take-over opportunity emerges for the big ones. Also, there are risks of new forms of exclusion created by cross-licensing practices if access to specific technologies is limited to a closed circle of incumbent firms (Deconinck, 2020). Finally, while more biotech-intensive applications hold promises regarding productivity increases, there are questions about whether the number of jobs created in biotechnology is substantial enough to compensate for the fact that some labor-intensive sectors might become obsolete (Eversberg, Holz, et al., 2023).

Moreover, even when we expect more collaboration and open innovation to develop technologies, these new technologies need to be transferred to improve well-being. To whom will these technologies be transferred, and under what conditions? Access to knowledge is necessary to help least-developed countries reach growth convergence. A well-designed value chain should help to transfer knowledge, but this might not occur without a minimum threshold of capabilities in the least developed countries (Gries et al., 2018; Janssen & Swinnen, 2019). Also, this could increase technological dependency in developing countries. Acemoglu (2002) suggests that technical change strongly biased towards skilled labor may increase the income gap between rich and poor economies, given that developed countries have the highest share of skilled workers.

1.7 Conclusions

A sustainable transition to a bioeconomy requires more than replacing fossil-based products. It calls for a shift in the current technological paradigm. This chapter proposed the concept of bioeconomy upgrading to describe trajectories that minimize negative environmental externalities and create new opportunities for adding economic value.

The first original contribution of this chapter lies in the systematization of an overarching typology of value chains in the highly dynamic landscape of the bio-based economy. This helps to answer the first research question, delving into which value chain features are more conducive to a process of intensified innovation leading to a bioeconomy upgrading. While many of the current debates focus mainly on primary production and biomass-intensive activities, a bioeconomy upgrading implies a broader range of activities, some of them biotech-intensive. Each of the six presented models shows different characteristics in terms of the technologies involved (from mature to completely new bio-based techniques) and how innovation takes place (from diffusion, which requires mainly organizational changes, to invention-innovation that demands research competencies and collaboration). The acceleration of innovation rates in the bioeconomy is associated with (a) shorter and tighter value chains with an increasing degree of vertical coordination; (b) enhanced role of big and leader firms and potentially more concentration, at least until new bio-based technologies become mature; and (c) more collaboration and knowledge sharing among value chain members, to move from turnkey to tailor-made technologies.

The second main contribution, tied to our second research question, is to introduce a discussion on the social sustainability dimension of a bioeconomy upgrading, for which empirical research is still limited. Future research should explicitly account for value chain organizational aspects in the bioeconomy to better assess the winners and losers of these innovation processes. This perspective is critical to understand to what extent a bioeconomy upgrading oriented to improve environmental sustainability may simultaneously create harmful side effects from a social perspective. For example, our models show that in low-volume and biotech-intensive value chains, farmers might obtain only a small share of the surplus created as downstream activities become more relevant. However, at the same time, opportunities to participate in new value chains might open for them (e.g., farmers do not have a role in the fossil-based plastics industry nowadays, but they might be able to participate in the bioplastics value chain).

Our work has implications for several private and government actors. From a business strategy perspective, companies should be aware that as the bioeconomy becomes technology-intensive, they need to strive to create both upstream and downstream markets and design governance mechanisms for rapidly evolving value chains. From a policy standpoint, while it seems hard to change the natural course of a technological transition, policymakers should consider measures to mitigate potential harmful effects from a social perspective. In this context, safeguarding the interest of the weakest value chain actors is critical, giving them access to these new bio-based technologies and ensuring they will not be left out of the bioeconomy. But while access to these technologies is an issue, it is also important to consider whether end consumers – be they farmers or households in urban centers – will embrace these biotech-intensive products and services. Complexity in using the technologies or difficulty perceiving their benefits can hinder adoption.

We are aware that one of the main characteristics of the bioeconomy is the convergence among economic sectors and the creation of dynamic value webs (Scheiterle et al., 2018). Biomass cascading use and knowledge sharing contribute to blurring the boundaries between industries. On behalf of simplicity and generalization, all the value chain maps in ***Figure 1.2*** were presented in a linear set-up, but we believe these models still represent the highly inter-industrial setting of the bioeconomy. Each of the proposed value chain maps is built by actors from different industries, and the same happens with biomass flows. For instance, in models 1-3, there are interactions between the food, feed, and energy industries. In model 4, we see how traditional chemical industries get into producing RE and bio-based products. The same happens in models 5-6, where companies with complementary capacities join to launch new products.

While quantitative and modeling approaches are useful to explore specific binary relations in value chains, qualitative perspectives are better for understanding the dynamics of entire value chains (Bellemare, 2022). This chapter presents an original comprehensive view of the challenges created by the transformation of value chains in the face of the promises of a bio-based economy. Nevertheless, there are three caveats in this study. First, a systematization based on typologies normally entails a degree of simplification. It is possible that many bioeconomy initiatives and business cases do not fit perfectly under any of the models that we proposed. Second, those models should be considered complements rather than substitutes: we expect that goods and industrial processes that rely on high-volume and low-value biomass will lose their economic importance, but some of the technologies discussed may be one-to-one substitutes while others do not. The rate of innovation in bio-based initiatives will accelerate, but all the presented models will likely coexist in an upgraded bioeconomy. Third, for a bioeconomy upgrading to be sustainable, we are assuming that biomass production is input-efficient and food has priority over the allocation of the available productive land. Sustainably produced biomass is a core principle of the bioeconomy, without which the bioeconomy could even create more environmental challenges than those it solves (Anlauf, 2023).

From a research perspective, there are still many opportunities to understand the causal mechanisms behind the interaction between value chains and innovation. Also, research efforts should be aimed at including social sustainability in the bioeconomy research agenda. The discussion of social sustainability aspects has lagged behind environmental sustainability in the bioeconomy literature. Hopefully, the conceptual framework presented in this chapter will guide future empirical research in the field of the bioeconomy.

Chapter 2 Technology-driven transformations in agri-food global value chains: the role of incumbent firms from a corporate venture capital perspective

Abstract: Agri-food GVCs are failing to provide healthy and affordable diets within planetary boundaries. Many cutting-edge technologies are being developed to address the sustainability challenges throughout agri-food GVCs. While several studies seek to analyze the impacts of specific innovations on socioeconomic and environmental dimensions, the relationship between industry structure and the process of technological change has not received much attention in the value chain literature. Here, we focus on the entrepreneurial landscape of innovation in agri-food GVCs to 1) identify which technologies have been receiving most support from investors and 2) analyze the corporate strategies of the largest agri-food multinational companies regarding their investments in new technologies. Using Crunchbase as our primary data source and machine learning for natural language processing, we have identified around 15,500 companies developing innovations linked to agri-food GVCs, from farming to last-mile delivery. However, our analyses show an imbalanced scene in which downstream technologies capture most investors' interest. Then, we use these results to explore the direction of investments by dominant agri-food firms, where we identify three trends: upgrading strategies to improve their core activities, defensive strategies to control technologies competing with their core business, and corporate portfolio strategies to seize profit opportunities.

Keywords: agri-food systems, innovation, global value chains, venture capital, industry structure, machine learning

2.1 Introduction

Global AFS are failing to provide healthy and affordable diets within planetary boundaries. Food systems are responsible for around one-third of anthropogenic greenhouse GHG emissions (Crippa et al., 2021) and are one of the main drivers of biodiversity loss (Read et al., 2022), mainly due to land-use change, excessive agrochemicals use, and depletion of water resources. Furthermore, from a social perspective, around 3 billion people cannot access affordable and healthy diets (FAO et al., 2022). This situation has worsened with the disruptions experienced in the last few years due to COVID-19 and the Russia-Ukraine war, which exposed the vulnerability of food value chains to shocks (Béné et al., 2021; Deininger et al., 2023).

As a result of these social and environmental pressures, we are currently seeing innovations aiming to steer AFS towards more sustainable pathways and make agri-food GVCs more resilient to various shocks. The convergence of biotechnology with digitalization and artificial intelligence is transforming food systems at the farm level and many other stages, including farming inputs, food processing, logistics, packaging, and retail. This is accelerating the structural transformation of agri-food global GVCs, which are becoming longer, capital-intensive, and with a higher relative share of post-farmgate activities in the value added (Reardon, 2015; Yi et al., 2021).

However, the introduction of new technologies is insufficient to ensure genuinely sustainable food systems, given the several challenges that technological change poses from a social perspective (Clapp, 2022; Klerkx et al., 2019). These challenges include unequal access to new technologies by final users (i.e., consumers or farmers), uneven benefit distribution, and displacement of smaller value chain actors, among many others (Finger, 2023; Hackfort, 2021). These issues are particularly relevant in agri-food value chains due to high market concentration rates (Clapp, 2021b; Sexton, 2013). We see evidence of industrial consolidation in food retail (Deconinck, 2021), commodity trading (IPES, 2017), seed biotechnology and agricultural inputs (Clapp, 2018; Deconinck, 2020), industrial food and beverage companies (Howard, 2016) and agricultural equipment (Fuglie et al., 2012). Thus, this new socio-technical regime in which innovation is revolutionizing food systems holds the risk of being held up by lock-ins from the current system (Geels, 2019).

Several papers have studied structural transformations in agri-food GVCs (C. B. Barrett et al., 2022; Reardon et al., 2019; Sexton, 2013). A recent and growing body of literature discusses the potential of new cross-cutting technologies to transform farm and post-farmgate stages (Birner et al., 2021; Bunge et al., 2022; Herrero et al., 2020, 2021). However, these two strands of literature look still disconnected, as the nexus between the literature on agri-food value chain literature and industrial organization in the context of technological change has not received enough attention (Bellemare, 2022; Macchiavello et al., 2022). This chapter seeks to fill this gap by exploring the links between technological innovations related to agri-food production, distribution, and consumption and the industry structure in agri-food GVCs. In specific, we look at the entrepreneurial landscape of innovation in AFS, covering the entire value chain (from farming inputs to last-mile delivery), and explore the potential influence of industry concentration in this technological transition. We use corporate venture capital investments to study the behavior of the large multinational firms that govern agri-food GVCs.

The research questions in this chapter are: (a) what are the leading technologies and solutions entrepreneurs are taking to the market in agri-food value chains? and (b) what type of investments are incumbent agri-food companies prioritizing as venture capitalists? The primary data source for our analysis is Crunchbase (2022), a comprehensive database of highly innovative public and private companies. We propose two main goals in this paper. The first is to characterize the innovation landscape in the global AFS based on the value propositions of emergent science- and tech-based firms. We do this by first creating a typology of the technological solutions that these firms are developing and then using machine learning (ML) for natural language processing (NLP) to classify the firms accordingly. This approach is more informative and detailed than the standard industry classification (SIC) codes usually used to categorize industries and companies. Our second goal is to use this typology to explore the direction of multinational agri-food firms' investments from a corporate venture capital perspective and analyze the role these dominant firms play in the technological transformation of AFS.

Following the distinction by Zilbermann et al. (2022) between innovation and product supply chains, the first question of the chapter targets the innovation supply chain level: we explore the technological solutions that promise to improve agri-food GVCs. However, this cannot be understood isolated from the industrial dynamics of agri-food GVCs, which will determine the success of many of these innovations when moving toward the product supply chain. While many small entrepreneurs (i.e., start-up companies) can come up with new solutions, upscaling and making them suitable for massive markets requires the commitment of incumbent firms in the product supply chain. This is why it is necessary to explore the role of dominant corporations in front of these new technologies (the second question in this chapter).

The remainder of this chapter is structured as follows: Section 2.2 summarizes the process of industrial consolidation experienced by agri-food GVCs in the last decades and why this matters in the context of technological change. Section 2.3 describes the data and methods used for our empirical analysis. Section 2.4 presents the results of our classification process and the investment flows by dominant firms in each category. Section 2.5 presents a discussion of the results, summarizing three general trends in the role of incumbent firms as venture capitalists. The last section of the chapter includes the main conclusions and business and policy implications.

2.2 Innovation, sustainable transitions, and the governance of agri-food GVCs

In the face of many environmental and social challenges, the acceleration of technical change in digitalization, biotechnology and artificial intelligence promises to improve the sustainability of agri-food GVCs by reducing the application of synthetic fertilizers and chemicals in agriculture (i.e., smart farming, farm robotics), improving crop yields with lower development costs (i.e., new gene-edited seeds), reducing the space needed to produce food (i.e., controlled environment agriculture), replacing the production of animal-based proteins (i.e., cellular agriculture, plant-based meats), enhancing food safety and traceability (i.e., blockchain technologies), reducing or reutilizing waste (i.e., biorefineries) and raising food accessibility and reach (i.e., e-commerce and last-mile delivery technologies), among many other promises.

However, technical change is not disconnected to the surrounding institutional environment (Geels & Schot, 2007). Innovations start at a niche level, and then the industrial, political, and social rules create the conditions for new technologies to scale and develop massively. In the last 30 years, agri-food value chains have experienced a process of structural transformation (C. B. Barrett et al., 2022; Reardon & Timmer, 2012). These structural transformations were part of a natural modernization process and adaptation to new demands and technological conditions. Still, at the same time, many of these changes have enhanced the role of multinational corporations in moulding the institutional setting and governance rules in every segment of GVCs. In a context where thousands of start-ups are driving innovation in AFS (Klerkx & Villalobos, 2023), understanding industrial dynamics is necessary to elucidate whether technology can deliver the promise of improving agri-food GVCs.

In the upstream segment, we have seen an increase in the potential of biotechnology for the farming sector. Modern seed biotechnology has enhanced the complementarities between seed and agrochemicals (Deconinck, 2020). This race to exploit and monetize these complementarities happened in the context of increased costs and risks of de-regulating new biotech events in seeds and agrochemicals (McElroy, 2004). As a consequence, we have seen in the last few decades a consolidation of the sector into a small group of companies (known as the big-six) capturing most of the market share and creating a cross-licensing scheme among them (Clapp, 2021a; Deconinck, 2019). That has become even deeper in the last few years, and now the big six have become the big-four[5]. A similar (but somehow less pronounced) dynamic occurred in the agricultural machinery and equipment sector, in which the leading companies increased their market shares in the last quarter of the twentieth century. Significant economies of scale and the need for global manufacturing and distribution facilities have reinforced the leadership of multinational companies (Fuglie et al., 2011).

Agricultural commodity trading has also been consolidated in the last few decades (Clapp, 2015), in which a small group of multinational companies control the lion´s share of grain exports[6]. The Chinese strategy to move into grain trade and other recent corporate movements[7] have further consolidated the sector (Ballard, 2016; Kelloway, 2023). The first reason behind this process is the natural spatial configuration of trade in GVCs, which requires high investments in fixed assets and infrastructure to process and transport grains. The second reason is related to the need for a solid financial structure for market hedging to deal with food price volatility, which has become more evident in the last 20 years mainly due to the nexus between food and energy markets and the massive irruption of investments funds in commodity markets (Salerno, 2017; Wright, 2011).

At the midstream level, many structural changes happened in food processing. These changes are related to changing consumption patterns and the appearance of new processed (and ultra-processed) food and ready-to-eat meals. As a result, farming activities have reduced the share in total food value-added against food processing and marketing (Canning, 2011; Yi et al., 2021). This has also led to a reorganization at the level of the food processing industries, with fewer and bigger actors acting as buyers at a global level (Muehlfeld et al., 2011; Ollinger et al., 2005). Moreover, consumers' demands for more information about the food they eat have brought into the scene institutional innovations to improve food traceability and sustainability aspects. Big food companies have worked to align the value chain by establishing stringent requirements for their suppliers in which private standards have played a relevant role (J. Lee et al., 2012; Meemken et al., 2021).

Finally, GVCs have also experienced structural changes in the downstream segment, close to final consumers. The expansion of supermarket chains across continents is known as the supermarket revolution (Reardon et al., 2012). Supermarkets have promoted new buying behavior by final consumers (Volpe & Boland, 2022) and have changed the dynamics of AFS, developing a pattern of buyer-driven GVCs (Gereffi, 1994; Gereffi & Christian, 2009). More recently, COVID-19 has also accelerated the e-commerce trend for grocery and food stores, a trend that had been clear for apparel and consumer products but arrived later at AFS (Reardon, Heiman, et al., 2021).

[5] This has happened through the acquisition of Monsanto by Bayer, the purchase of Syngenta by ChemChina and the merger between Dow and DuPont (now Corteva).

[6] This companies are known as the ABCD, in reference to the initials of ADM, Cargill, Bunge and Dreyfus.

[7] In 2017, the Chinese trading company COFCO completed the acquisition of Nidera. Recently, the companies Bunge and Viterra merged.

The structural transformations described in this section explain the morphology of value chains as we know them today. Agri-food GVCs have experienced a consolidation process in most stages[8], where now global multinational corporations play a central role in establishing governance patterns. Although it is out of the scope of this study to understand whether this concentration process resulted in a practical exercise of market power, we have to acknowledge the important role that industry structure plays in the process of technical change, which is often presented as one of the pathways through which global agri-food value chains may tackle many sustainability challenges. The success of this set of innovative solutions that promise to revolutionize AFS is highly dependent on industry dynamics since governance rules affect how learning and technology transmission take place in GVCs (Pietrobelli & Rabellotti, 2011). The innovation and technology selection patterns are not independent of industrial characteristics such as concentration rates, firm asymmetries, and market share variability (Dosi et al., 1995; Dosi & Nelson, 2010; Marsili, 2001). Leader firms in agri-food GVCs can prioritize technology canons, control global distribution networks, establish production standards, and cater to consumers' preferences (Béné, 2022; Clapp, 2021b).

The main contribution of this chapter is to provide a comprehensive analysis of technical change in agri-food GVCs, comprising every step in the value chain, from farming to final consumers. Agricultural economists have successfully studied dyadic relations in value chains (e.g., farmers-input suppliers, farmers-processing companies), but new methods and perspectives of analysis are needed when it comes to understanding the entire value chain (Bellemare, 2022). And this is especially true when studying innovation, which demands a prospective analysis that cannot rely easily on historical data. Even when we cannot make claims about how industry dynamics will evolve and whether new structural changes will happen, we can still explore and classify the main innovations taking place and delve into the role of agri-food incumbents, getting hints on their strategic intentions through corporate venture investments. The following section describes the data and methods in detail.

2.3 Data and methods

This chapter uses Crunchbase as its primary data source. Crunchbase (2022) is a comprehensive database of highly innovative public and private companies, including data on organizations, people, and investors. The main goal of the database is to facilitate the research process of corporate venture capitalists seeking to invest in young companies, as well as the interaction among founders and workers in those companies. In recent years Crunchbase has been increasingly used for academic research, particularly in Economics and Management (Dalle et al., 2017). Many recent papers use this database to provide evidence of sustainable transitions with diverse goals and methods (Kwon et al., 2018; Marra et al., 2017; Tiba et al., 2021). This database allows us to identify and classify companies innovating in agri-food GVCs and map incumbent firms' investments in these companies. In this section, we describe our methodology step by step:

a. Deductive stage

We start our methodological approach by listing the most prominent startups and young companies working with innovative technologies at different stages of agri-food GVCs. This set of around 500 companies (detailed in Supplementary Material 1[9]) works as a gold standard that guides us in

[8] We have some exceptions to this consolidation process such as the farming level, which is still consist of a big base of farmers from different sizes and some local transport, logistics and processing activities show also low degrees of concentration but are highly dynamic (Reardon, 2015).

[9] All the Supplementary Materials in this chapter are available in the following link.

identifying all other firms in the dataset and then classifying them[10]. The selection of these companies was made following specialized industry reports[11].

We then produced a preliminary-deductive typology of innovations in AFS based on an exploratory literature review (mainly through Web of Science and Scopus), including reference snowballing to identify further relevant articles. We looked for papers discussing innovations and technologies in different segments of food value chains to summarize and consolidate them in our own typology of innovations. We did not focus on specific technologies but rather on "solutions", considering that every technological platform can become the building block for multiple solutions in different value chain stages[12]. The complete list of papers we consulted to build the typology is detailed in Supplementary Material 2. This preliminary typology went through several rounds of fine-tuning at later stages. We started with a more detailed classification of around 35 solutions and then merged the ones that were more similar or that could be placed under a broader category. This fine-tuning process aimed to balance the need for a descriptive and informative typology (which demanded a higher number of categories) and the efficiency of the subsequent machine learning classification (which required reducing the number of categories). The final version of the typology is presented in ***Figure 2.1*** (See **Appendix 2 *1*** for the details and definitions of each category).

b. Database query

Next, we run a first query in Crunchbase to preliminarily identify companies working on solutions related to agri-food GVCs. The original number of companies listed in Crunchbase is above 2 million. The database includes general information about each company (i.e., country, city, address, date of foundation), a company description paragraph, tags that provide keywords synthesizing the company's activities in one or two words, and information on funding (e.g., number of funding rounds, total accumulated funding). Each company has a unique identificator (called *uuid*) that can then be used to match the company with people, funding rounds, or investors[13].

With the help of the R package *corpustools* (Welbers & Van Atteveldt, 2022), this search combined two fields: company descriptions and tags (see Supplementary Material 3 for more details). In this first exploration of the Crunchbase database, we identified around 26,400 potentially relevant companies. In addition, companies in the Gold Standard that did not appear in the query were added manually. The process is summarized in ***Figure 2.2***.

[10] The condition to be included in the gold standard is that these companies had to be listed in the Crunchbase database at the moment of download (January 2, 2023).

[11] Among the industry reports that we used to build this list, we can mention the ones by AgFunder (2022), Forward Fooding (2022), SVG Ventures (2020), The Good Food Institute (2021) and The Yield Lab (Navarro et al., 2022).

[12] For example, the Internet of Things (IoT) can be the building block for crop sensors, packaging devices or kitchen appliances. Artificial Intelligence is being applied in farm robotics and other devices at the farming level but also for autonomous delivery vehicles in the downstream segment of the value chain.

[13] Each element in the database has a unique identificator (i.e., companies, people, funding rounds, investors). Through the use of these identificators one can connect, for example, a company with the funding rounds in which this company was involved, or a funding round with the investors that participated in it.

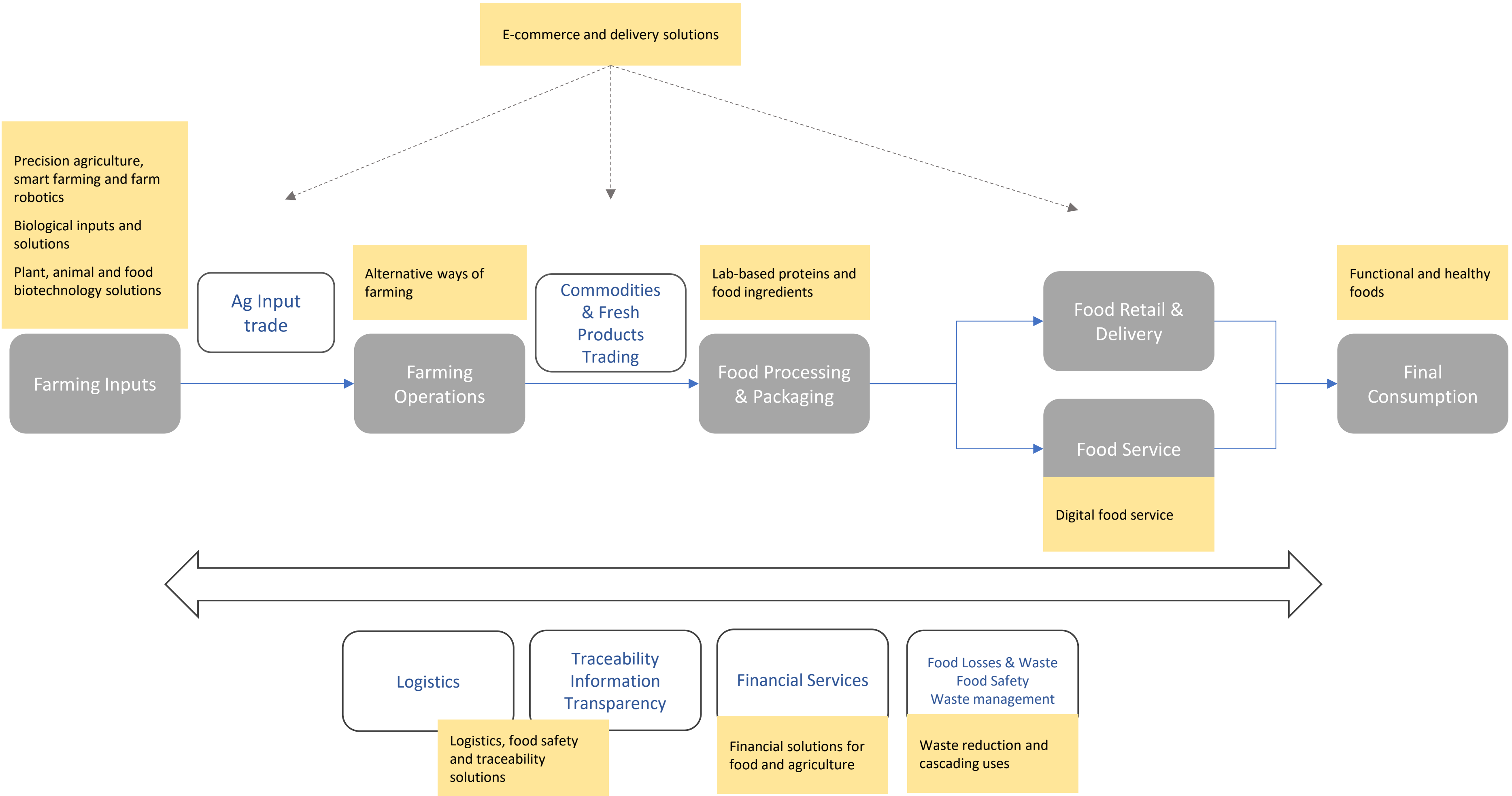

Figure 2.1. Typology of innovations in an archetypal agri-food value chain.
Eleven different types of innovative solutions are presented in the yellow squares. Gray boxes represent structural functions in a value chain. White boxes represent functions that do not belong to a specific stage but rather connect stages or are performed across stages.

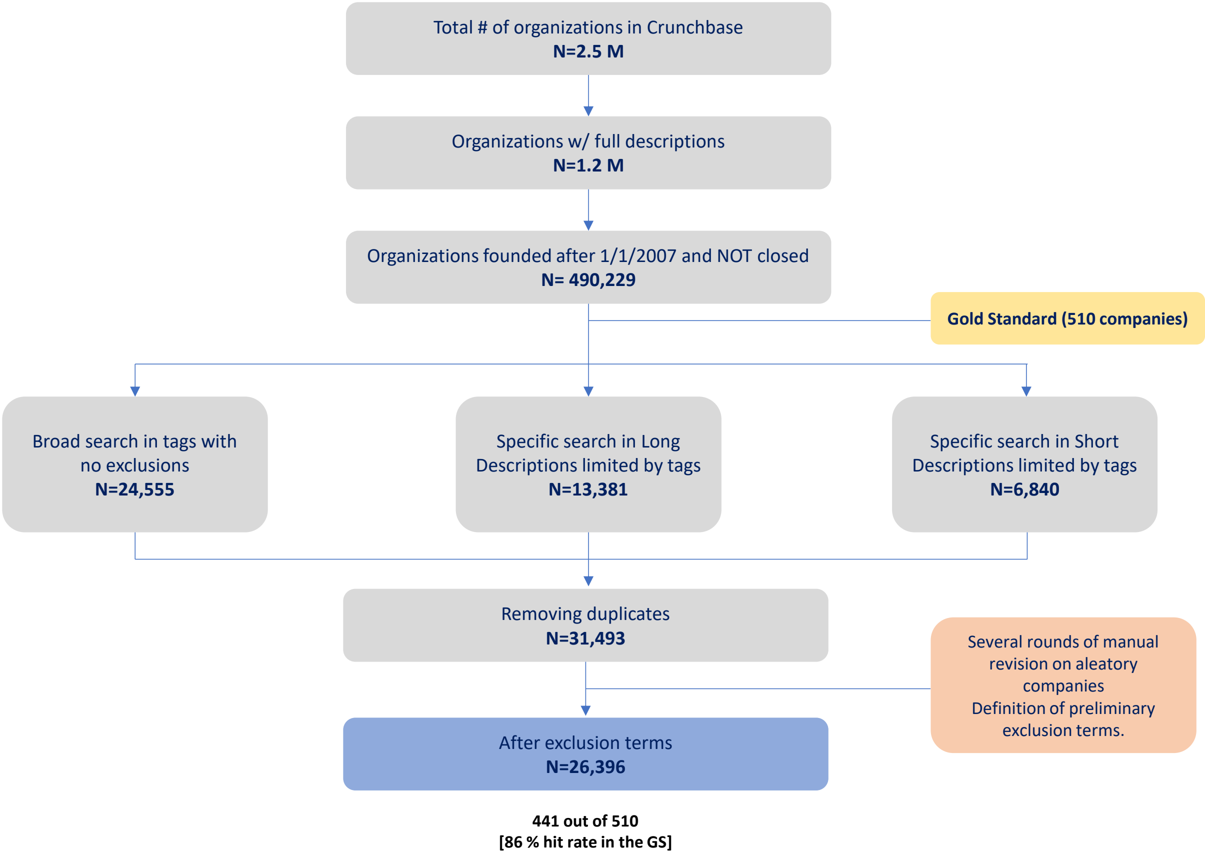

Figure 2.2. Database Query.

c. Data preparation and cleaning

For these 26,400 preselected companies, we combined the long and short description fields in Crunchbase and turned them into a text corpus. Then, we tokenized and cleaned this text corpus (Benoit et al., 2018). Each token is a smaller piece of text, a sequence of characters that serve as units for the analysis (Manning et al., 2009). Tokens can be individual words, compound words, or even symbols, depending on the research goals. We worked with n-grams of size 1 or 2, removing symbols, numbers, punctuations, and URL addresses to turn the corpus into tokens. We also removed English stopwords[14] and tokens of less than three characters to reduce the noise in the text corpus. Every token was then turned to lowercase, and we kept only word stems.

Finally, we built a document-feature matrix (dfm), the base for the analysis, in which documents (i.e., in our case, company descriptions) are listed in rows while tokens are in columns. A dfm is a sparse matrix that shows the frequency for each token in each document. We weight the dfm by the term frequency-inverse document frequency (tf_idf) to reduce the weight of terms that are too frequent (and do not provide much information for the classification stage) and increase the weight of terms that are specific to a document and may provide valuable information (Manning et al., 2009). The tf_idf weighting follows the form:

$$tf\_idf_{t,d} = tf_{t,d}\left(\log\frac{N}{df_t}\right) \tag{2.1}$$

[14] Stopwords are very common terms that operate as connectors or auxiliary words. These words are used so often in the language, that do not add substantial information in a NLP setting. Examples of stopwords in English are words like "I", "me", "we", "our", "were", "this", "that", "be" or "do" among many others. R packages oriented to text mining normally include a set of stopwords or the possibility to import it.

Where $tf_{t,d}$ is the frequency of term t in document d, N is the total number of documents and df_t is the total frequency of the term t in the text corpus (sum of appearances in all documents). Supplementary material 4 shows a detailed example of this process using the package *quanteda* (Benoit et al., 2018), from building the text corpus to the final weighted dfm matrix.

d. Algorithm training

We started the inductive process by manually classifying companies. First, we categorized companies in the gold standard, and later we classified 4,783 additional companies taken randomly from the Crunchbase query. Consequently, we reached a total of 5,293 companies manually labeled (around 20% of the entire query) (**Appendix 2** ***2*** shows the final classification for this annotated dataset). This process was based exclusively on Crunchbase descriptions[15]. We also established criteria to exclude companies irrelevant to our classification despite being included in the initial query (Supplementary Material 5 for more details). Finally, we used some of the tools provided by the package *litsearchr* (Grames et al., 2019) to identify the most common compound words and added them manually to help train the algorithms[16].

e. Classification

We used a set of ML models to classify companies according to the kind of technology they develop. We used the manually labeled group of 5,293 companies as our base to train the algorithms, with the final goal of accurately predicting the class membership of each company outside the manual review sample. We divided the classification problem into two parts. In the first stage, we worked with a binary classification problem, in which we wanted to automatically exclude companies irrelevant to the analysis despite being included in the initial query (Supplementary Material 5 shows a list of the type of companies that should be excluded). After this stage, we moved to a multilevel classification problem, in which we classified the surviving companies into the 11 categories presented in **Figure *2.1***.

Not every ML algorithm works well in a multilevel classification problem with text data as input, so we selected those more suitable for this purpose. Benoit et al. (2018) include Naïve Bayes (NB) and Support Vector Machine (SVM) in the *quanteda* R package. NB classification is based on Bayes' conditional probabilities theory and uses each token as a feature to predict the outcome. This algorithm assumes that all predictors are independent and they have equal effects on the outcome (Loukas, 2020), which are strong assumptions and not always realistic (this is why it is called "naïve"). Nevertheless, it is a simple and flexible option for ML classification and it is often used to solve real problems (James et al., 2013). SVM is a classification algorithm that can be used in linear and non-linear settings, based on separating hyperplanes to split a set of observations in different categories (Noble, 2006). The points nearest to these division hyperplanes are support vectors and the reference to maximize the distance between categories. Despite their simplicity, NB and SPV are efficient for working with small annotated datasets (Riekert et al., 2021).

Hvitfelds and Silge (2022) also provide an example of regularized linear models for multilevel classification (LASSO) using the R package *tidymodels*. Despite not being cutting-edge for NLP, linear

[15] We did not consult company websites, social networks, or any other external sources.
[16] We included compound words that were found very often in each category, but also that meant something in terms of the analysis. For example, we included compound words such as "active ingredient*", "blockchain technolog*", "circular economy", "anaerobic digestion", "cellular agriculture", "plant-based meat", "indoor farm*", "synthetic biolog*", "gene edit*", "soil microbiom*", among many others.

models are still helpful in practice. LASSO runs a quadratic problem minimization to shrink some regression coefficients (even turning some of them to 0) to retain only the most important features (Tibshirani, 1996). We also used an unsupervised technique called topic modeling based on the Latent Dirichlet Allocation (LDA) algorithm to improve the algorithms' accuracy in the linear setting. LDA is based on the idea that a corpus of text represents latent topics characterized by a specific distribution of words (Blei et al., 2003). This technique seeks to identify topics within the data based on the words of the text corpus and assigns a probability for each document belonging to each topic (Watanabe & Müller, 2023). We took these probability vectors and included them as input in the linear model.

We compared the performance of these algorithms based on two of the most commonly used measures in classification problems. The first is prediction accuracy, which measures the rate of correct predictions over total predictions:

$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + False\ Positives + True\ Negatives + False\ Negatives} \tag{2.2}$$

The second measure is the area under the Receiver Operating Characteristics curve (ROC AUC), which is the relationship between two measures:

$$True\ Positive\ Rate\ (TPR) = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{2.3}$$

$$False\ Positive\ Rate\ (FPR) = \frac{False\ Positives}{False\ Positives + True\ Negatives} \tag{2.4}$$

The ROC curve plots the TPR against the FPR at different probabilistic threshold levels, and the ROC AUC is a measure of the area under that curve (James et al., 2013). The closer to 1, the better the algorithm works. A value of 0.5 shows that the algorithm is doing no better than a random assignation.

Crunchbase descriptions show considerable variability in terms of the depth and quality of the information included. While some companies have comprehensive details of what they do, their goals, and which value chain actors they are targeting, other descriptions are short and do not allow a straightforward interpretation of what the company does (see Supplementary Material 6 for specific examples). **Appendix 2 *3*** presents a word cloud and a co-occurrence network for the most common tokens in our text corpus. Given the nature and size of our data and considering that each ML model prioritizes different parameters and is likely to classify companies differently, we used and compared different models to check how well they agree. Thus, we made the final classification based on a multi-model agreement, with manual control in various stages, to reduce the chance of misclassification. In the results section, we present the details of the final classification.

f. Analysis of venture capital flows

Finally, based on the reports by IPES (2017) and ETC Group (2022), we listed a group of incumbent industry leaders in AFS. These companies have the highest market shares and dominate each stage of agri-food GVCs. Many young innovative firms may undergo several years without genuine income before monetization starts, so they rely on venture capital inflows to support the transition (Kaul, 2021). Large corporate investments are one of the possible sources these firms can use, which also constitutes an opportunity for incumbents to participate in smaller (and sometimes more dynamic) science- and tech-based firms.

Based on our previously defined typology and classification, we analyzed the funding rounds in which these companies have been involved as investors to describe the direction of their corporate investments. These companies belong to different industries, such as agrochemicals and seed, veterinary pharma, farm machinery, commodity trading, food and beverage, meat and proteins, and grocery retail (**Appendix 2 *4*** shows the complete list of incumbents considered in our analysis). This way, we can understand the strategic focus of these companies as investors, exploring which categories in our typology they are addressing with more interest.

2.4 Results

a. Classification of companies

The purpose of the classification process was to arrive at a set of companies considered relevant in terms of our research goal (i.e., companies that create innovations in different stages of the agri-food value chains), each of them assigned into one of the 11 categories that we proposed in our typology of solutions. In the first step of the classification problem, we started with 26,465 companies. Of this group, 5,293 were manually classified (in this case, as either relevant or non-relevant) and operated as the training set. We selected the three algorithms with the best performances (NB, SVM, and LASSO plus topics from the LDA analysis) and used these algorithms both for the binary and the further multiclass steps[17]. **Table *2.1*** summarizes the performance measures for these three algorithms, which outperform the null model[18].

Out of the 21,172 companies in the classification set, the three algorithms matched for 15,872 cases. In 5,300 cases, two algorithms agreed, while the third did not. In these cases, the companies were classified according to the agreeing algorithms. **Figure *2.3*** summarizes this process.

Table 2.1. Results for the classification problems (binary and multiclass)

	Binary stage				Multiclass stage			
	Null model	**NB** *quanteda*	**SVM** *quanteda*	**LASSO + Topics LDA** *tidymodels*	**Null model**	**NB** *quanteda*	**SVM** *quanteda*	**LASSO + Topics LDA** *tidymodels*
Accuracy	0.570	0.806	0.795	0.776	0.160	0.731	0.750	0.753
ROC AUC	0.500	0.787	0.783	0.856	0.500	0.784	0.803	0.955
Size of the training set	5293 companies				3056 companies			

[17] We also tried more sophisticated ML models seeking to improve the accuracy in the classification. However, these performed worse than the three algorithms selected. **Appendix 2 *5*** summarizes the results for all these other models and compares them with the three models that were selected for the analysis.
[18] The null model represents a random classification of the companies.

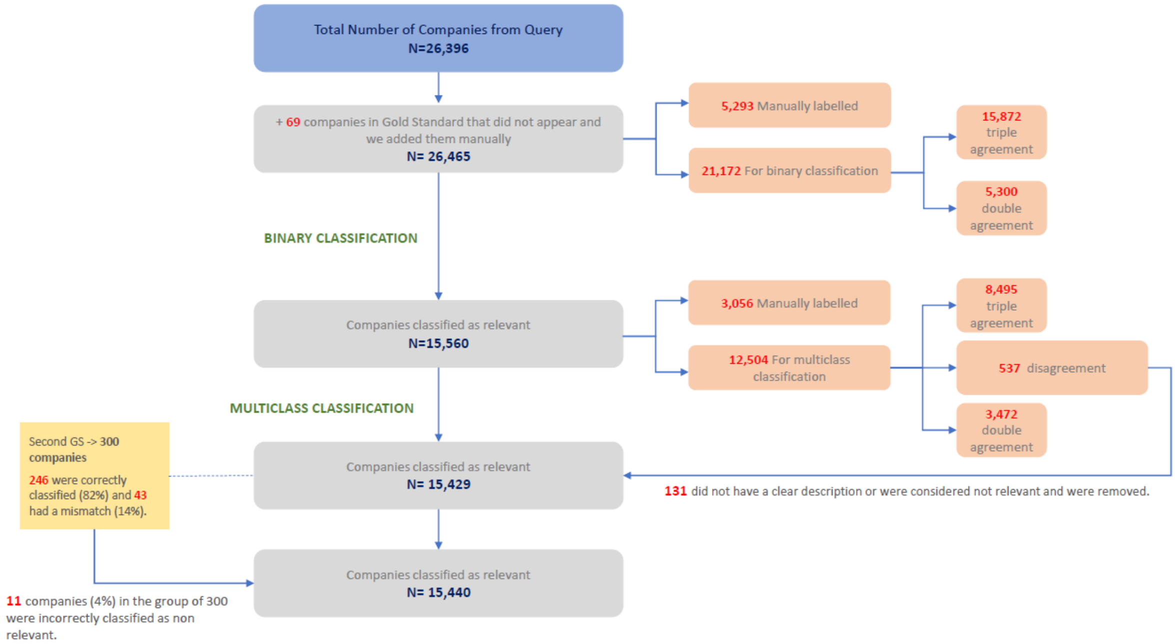

Figure 2.3. Classification of companies based on different machine learning algorithms.

After the first classification stage, 15,560 companies were considered relevant to continue in the analysis and moved to the next multilevel classification problem. Out of this set, 3,056 were already classified in the manually annotated group, whereas 12,504 were the target for classification. We applied the same three algorithms as in the first-stage classification problem (the results are in **Table *2.1***). The results of the three selected algorithms (NB, SVM, and LASSO plus LDA probabilities) show that the accuracy rates are above 0.7 but do not go beyond 0.75. Considering the particularities of our text corpus and that the accuracy rate in the null model (i.e., random classification) is around 0.16, we can say that the algorithms are doing a fair job despite potential mistakes in the final classification. Moreover, the performance levels of our algorithms are comparable to those found in other studies that use similar approaches (Qureshi & Sabih, 2021; Rabby & Berka, 2022; Sebők & Kacsuk, 2021).

Out of the 12,504 target companies, 8,495 had a triple agreement between the three algorithms. In 3,472 cases, there was a double agreement and one disagreement, so these companies were classified according to the agreeing algorithms. A number of 537 companies presented a triple conflict (each algorithm placed them under a different category) and were manually reviewed and classified, removing 131 due to incomplete or inaccurate descriptions. We also created a second manually classified gold standard based on different industry reports. This gave us an additional stage of control for the automated process. Out of the 300 companies in this second gold standard, 82% were accurately classified[19]. The fact that we are simultaneously applying multiple algorithms does not eliminate the possibility of misclassification but helps reduce the individual error rate of each algorithm.

The final classified set for analyzing investments and funding rounds comprises 15,440 companies. In

[19] We manually corrected the ones that were misclassified (14% of the total) and reintroduced 11 companies (4%) that had been incorrectly excluded in the first stage of the classification problem.

Table 2.2 we show that around 60% of the companies in our sample belong to downstream activities such as digital food service, functional and healthy foods, and e-commerce solutions. These activities are more related to the final consumer and the last-mile stage of value chains. Then, around 25% of the companies belong to activities related to the initial stages of the value chain and the farmer (precision agriculture, alternative ways of farming, biotechnology, and biological inputs). Finally, the rest of the companies are more oriented to midstream activities that range from food processing, logistics, waste management, and food waste reduction and financial solutions.

Table 2.2. Final classification of the relevant set of companies.

Class	**n (%)**
Digital food service	3,225 (21%)
Functional and healthy foods	3,109 (20%)
E-commerce and delivery solutions	2,791 (18%)
Precision agriculture smart farming and farm robotics	2,073 (13%)
Alternative ways of farming	1,143 (7.4%)
Logistics food safety and traceability solutions	950 (6.2%)
Waste reduction and cascading uses	910 (5.9%)
Lab based proteins and food ingredients	479 (3.1%)
Plant animal and food biotechnology	408 (2.6%)
Financial solutions for food and agriculture	182 (1.2%)
Biological inputs and solutions	170 (1.1%)
Total	**n = 15,440**

Figure *2.4* shows the accumulated and average funding (in millions of dollars) in each category. E-commerce solutions are clearly at the top of both rankings. These companies, mostly oriented to the last-mile delivery stage, are raising the highest interest from investors and capturing most of the funds. Digital food service is the second category for accumulated investments in funding rounds. Upstream-oriented technologies such as biotechnology, biological inputs, precision agriculture, and smart farming are still behind.

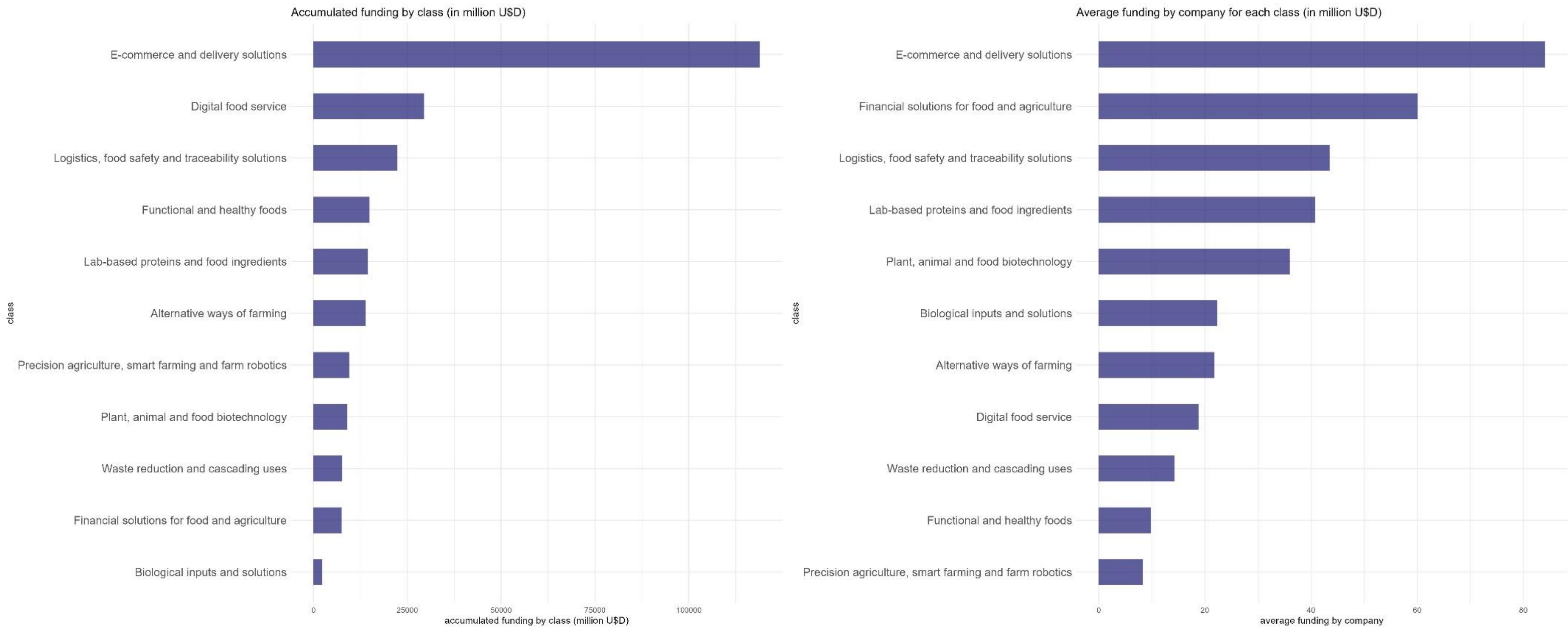

Figure 2.4. Accumulated funding and average funding in each category.

b. *Investments by agri-food incumbent firms*

Now we move to the results regarding the investments by dominant firms, our second research question. The approximate size of the investments by this group of firms reaches around 4.2 billion dollars[20] in the last 15 years, which is small compared with the total size of approximately 220 billion dollars[21] in our sample. The leading investors in our final selected group of companies are not incumbent firms but private equity funds, investment management firms, and sovereign funds and banks. These investors target startups entering a growth stage with proven products or services and markets developed. Despite not being the leading investors, the investments by dominant firms have an interest given their strategic nature, considering these multinational firms substantial mrket power to set the rules in agri-food GVCs.

In ***Figure 2.5***, we summarized the direction of the investments from the incumbents' sector to each of the 11 categories in our classification. In this figure, we have pondered each investment according to the size of the funding round they belong to, and we notice that e-commerce has the largest share. **Figure *2.6*** is similar but without ponderation, showing the results regarding the number of investments regardless of their size. This analysis is still important since many investments may not be large in terms of money but are strategically relevant. Here, we notice that the segments capturing most of the attention of investors are e-commerce, lab-based protein and food ingredients, and precision agriculture technologies. Both figures help describe the landscape of incumbents' corporate venture capital movements.

Figure 2.5 shows that investments by grocery retail corporations in the e-commerce and delivery segment look clearly more prominent than the rest of the flows. This is related to the substantial investments made by Walmart in developing e-commerce activities in India (Reardon, Heiman, et al., 2021). The most significant investments were in the equity rounds in Flipkart (later acquired) and Ninjacart. Other big supermarket chains have invested in e-commerce and logistics companies, such as Rewe in Flink or Kroger in Nuro. Large commodity trading multinationals have also been intensively active in terms of investments. The involvement of COFCO in the Chinese company JD Digits, which provides digital solutions to financial and commercial industries, explains the flow toward the category "financial solutions for food and agriculture." Cargill investments in Local Bounti, a company that produces vegetables in greenhouses, and InnovaFeed, an insect protein company, explain most of the flow toward the "alternative ways of farming" category. Finally, companies like ADM and Louis Dreyfus have shown interest in the alternative food and ingredients business through investments in synthetic biology companies such as Spiber and Motif.

Agricultural inputs companies are also active investors, but more in terms of the number of investment deals rather than their size (***Figure 2.6***). Most of their investments are primarily toward their core target segment, farming activities. They invest in startups developing robotics and artificial intelligence to detect pests and weeds or enhance precision in chemical applications, plant

[20] This is an approximate number that comes assigning each investor the same share of a funding round (total of the funding round divided by the number of investors registered in the funding round). This is a strong but necessary assumption since Crunchbase does not provide information about the individual share of each investor in the funding round.

[21] This is an approximate number considering all those funding rounds that have information in terms of quantity in Crunchbase. Part of the funding rounds are registered in the database but do not present information of their size.

biotechnology companies, and bio-input companies that aim to make crop protection and nutrition more sustainable.

We also see investments by agricultural input and commodity trading companies in technologies that will improve their ways of commercializing their products and increasing their base of customers, mainly agribusiness marketplaces based on e-commerce technologies. For example, the synthetic fertilizer company Yara, the agricultural input leader Syngenta and the commodity trading company Bunge are among the group of investors in the agribusiness marketplace Agrofy. Commodity trading companies Cargill, ADM, and LDC are investors in the Brazilian Grão Direto, where Bayer is also participating.

In the next section, we summarize these investments by multinational agri-food corporations into three general strategic trends and discuss their rationale.

Figure 2.5. The direction of investments by incumbents (pondered by the average size of FR).

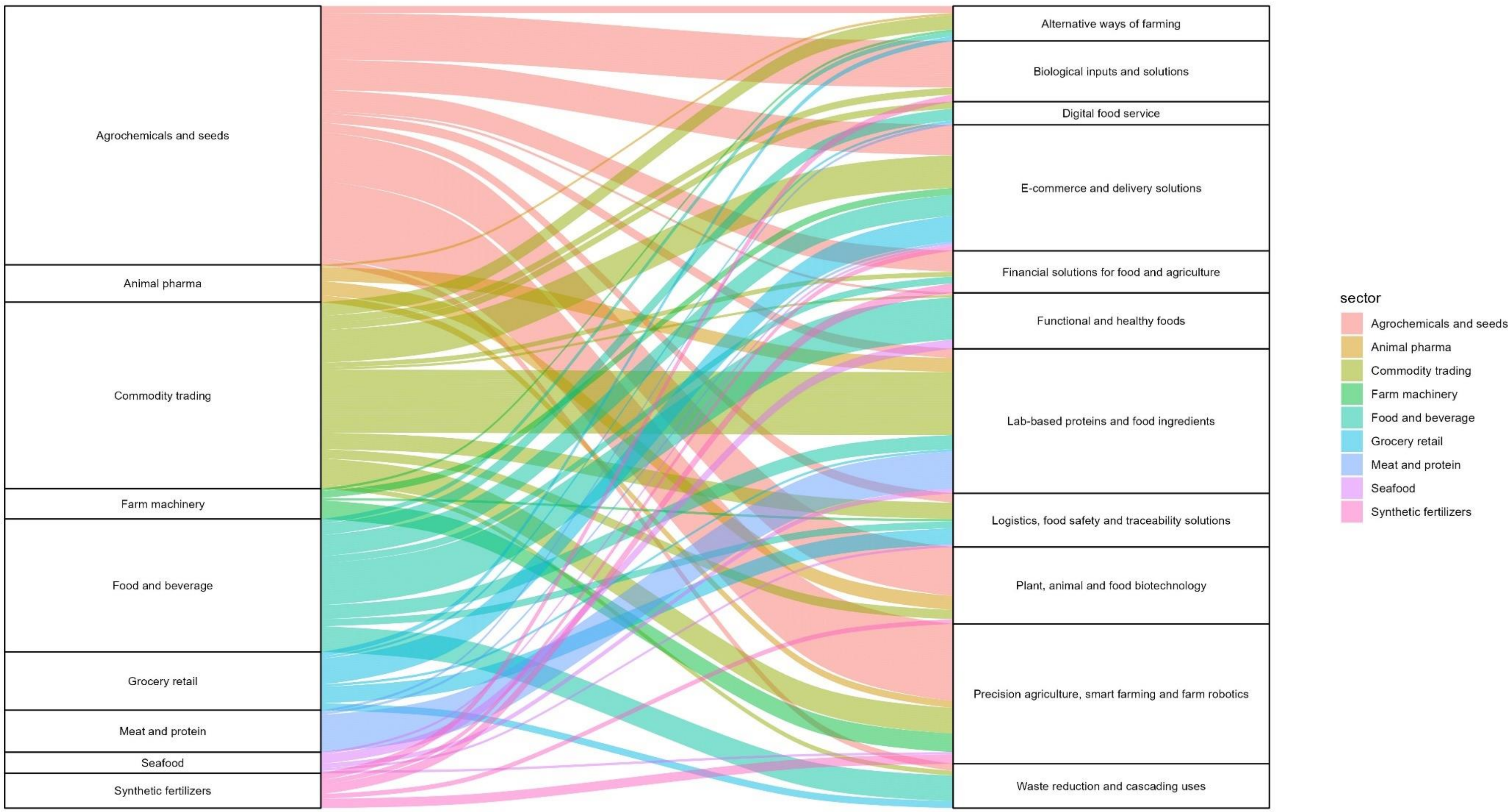

Figure 2.6. The direction of investments by incumbents (without ponderation, only in number of investments)

2.5 Discussion

a. *Innovation and investment flows: Are we placing efforts correctly?*

Regarding our first research question, which seeks to understand the landscape of innovations in agri-food GVCs, we notice that most companies in our sample (and most of the investment funds) flow toward downstream segments, more related to final consumption. In terms of attractiveness for investors and companies, upstream and downstream startups seem to be playing a different ballgame: the size of a medium or small funding round in the segment of e-commerce or digital food service may even outperform the largest financing round in upstream companies, such as seed biotech or farming technology (AgFunder, 2022).

Two reasons explain these differences. The first relates to technological maturity: solutions for the downstream segments lean on building blocks (i.e., digital technologies for mobile phones) that are much more mature than other technologies in the upstream segment, such as farming robotics, bioinputs, or alternative proteins. In this sense, technologies downstream in the value chain appear as the low-hanging fruit for investment funds, with lower risks, faster investment returns, and more startups offering opportunities to channel funds. The second reason is that the potential of digital technologies to boost sales and provide quick access to massive markets in the downstream segment is high compared to other upstream technologies, in which the challenges for developing markets are multiple (e.g., selling new gene-edited crops to farmers entails complex technical and commercial challenges compared to selling groceries to final consumers in a medium or large city).

This initial picture of the innovations in the AFS leads to a debate: are innovation efforts and investment funds flowing toward the value chain segment with the highest potential for improving sustainability in GVCs? Venture capital is crucial to supporting innovative startups, but it also presents biases toward innovations that fit the requirements of investors (Lerner & Nanda, 2020). In the last few years, even when the availability of funds has increased, part of the venture capital has become more risk-averse, seeking companies that foresee a fast exit through IPO or acquisition (Mazzucato & Perez, 2023). Companies related to e-commerce, last-mile delivery, and restaurant technology more easily fulfill those investors' requirements.

E-commerce technologies have played a significant role in mitigating value chain disruptions during the peak of COVID-19 (Chenarides et al., 2021; Guo et al., 2022) and can also contribute toward improving the nutritional quality of households through better food accessibility (Shen et al., 2023). Nevertheless, the potential of these technologies for improving the environmental sustainability of AFS seems limited. For example, food delivery technologies promise to reduce energy use and GHG emissions compared to individual research trips, but the evidence for a solid comparison of the mitigation potential with a baseline scenario is still scarce (Bunge et al., 2022).

Upstream activities related to the farming stage explain around 61% of the anthropogenic emissions created by food supply chains and are also the primary source of other environmental adverse effects, such as eutrophication and acidification (Poore & Nemecek, 2018). Therefore, technologies that support more sustainable food and biomass production by increasing yields and enhancing carbon capture hold a high mitigation potential (IPCC, 2023). Digital technologies at the farming level improve weed and insect control, promising reductions in the application of synthetic herbicides and fertilizers (Finger, 2023). Moreover, interventions at the upstream level to improve water management, soil fertility, and crop protection also have a social sustainability potential to lift people out of hunger (Chichaibelu et al., 2021).

Land use change explains most of the GHG emissions from agricultural production, in particular, linked to livestock production (Alexander et al., 2015). Considering that half of the habitable land is currently used for food production (Ritchie, 2017), upstream technologies oriented to the more efficient use of space, such as replacing animal proteins and producing in controlled environments, also hold a sustainability potential for mitigation (Bunge et al., 2022). Moreover, management technologies for producing livestock under more regenerative practices, and improving carbon capture through afforestation and reforestation, promise considerable carbon offsets. (Costa et al., 2022). Finally, considering the projected impacts of climate change on agricultural yields (Wing et al., 2021), it makes sense, from an adaptation perspective, to invest in technologies that reduce abiotic stress in crops (i.e., drought or severe temperature variations).

b. The rationale behind the investments by global agri-food incumbent firms

Our second research question was related to the role of agri-food multinational corporations as investors in technological firms. In this section, we try to explain the rationale driving their investment behavior. Given the trends that we see in the data, we can make some inferences about their potential strategic motivations. We identify three main trends: (a) upgrading strategies, (b) adaptation or control strategies, and (c) opportunity strategies, summarized in **Figure *2.7*** and described in detail in the following lines. **Appendix 2 *6*** includes a detailed list and examples of these strategies.

Upgrading strategies. Several incumbent firms invest in technologies that may likely boost or streamline their core business operations. We call these *upgrading strategies*. These strategies represent around 57% of the investments by incumbents in startups. The first explanation for these strategies originates from technological complementarities. Instead of doing R&D internally, incumbents invest in smaller actors with higher innovation rates to secure a future option for introducing those technologies in their companies (Dushnitsky & Lenox, 2005). By doing this, dominant firms avoid limiting their innovation process to their research divisions but can access a broader scope of technologies developed by smaller firms.

A salient case is incumbents that commercialize farm machinery investing in precision agriculture and smart farming companies. Some of these new developments in precision agriculture will likely reach the farmer incorporated as gadgets in traditional agricultural equipment (McFadden et al., 2022). For example, John Deere has invested in Innerplant, a company that is recoding plant DNA to make signals of distress visible through field machinery and satellite imagery, AGCO has invested in Greeneye, a startup working on deep learning applied to pest control, and Kubota has invested in the drone company Tevel Aerobotics. In this same line, agrochemical and seed companies may profit from the information that precision agriculture creates to provide additional services to farmers based on more efficient and personalized applications. For example, BASF has invested in farm robotics companies such as EAVision and Ecorobotix, Bayer has invested in the carbon mapping company EarthOptics, and Yara, one of the leading companies in the synthetic fertilizers industry, has invested in Sabanto Ag and Taranis, companies developing autonomous agriculture applications. For dominant agrochemical, seed, and fertilizer firms, accessing these technologies implies moving from selling standardized inputs to offering personalized services for farmers (Birner et al., 2021; Dickson et al., 2019).

A second reason driving upgrading strategies is related to market reach. Incumbent firms may invest in startups that help increase their market shares and improve access to final consumers. In the last few years, we have seen companies traditionally focused on the upstream segment of the value chain (such as agrochemicals, seeds, fertilizers, farm machinery, and commodity trading) investing in e-commerce companies that work as agribusiness marketplaces through which farmers have access inputs, hire or purchase machinery, sell second-hand machinery or even sell their products directly to processing industries or consumers (Birner et al., 2021). For example, ADM, Cargill, LDC, and Bayer are all investors in the Brazilian marketplace Grão Direto, John Deere has invested in Hello Tractor, CLASS in e-farm.com, and Bunge and Yara are investors in the Argentine digital marketplace Agrofy. These marketplaces are helping to reduce transaction costs, reduce the number of intermediaries in food value chains, and facilitate access to farmers for dominant firms. Something similar happens downstream in the value chain: retail grocery stores (traditionally brick-and-mortar) have made significant investments and acquisitions in e-commerce companies, such as Walmart in Flipkart or Ninjacart. These examples belong to a set of pivoting strategies that COVID-19 brought to the main scene, in which traditional companies owning physical facilities have turned massively into digital operations (Reardon, Belton, et al., 2021; Reardon, Heiman, et al., 2021).

Adaptation or control strategies. A second group of investments we have identified (around 31% of the total) is related to dominant firms funding technologies that compete and may (potentially) replace their core business. These technologies have a disruptive potential over the incumbents' core businesses and may force them to eventually re-arrange their business strategies. The underlying reasons for these investments are unclear beforehand, so we use the broad name "adaptation or control." In some cases, this might be related to the desire to adapt to new consumer demands and requirements for products that are less harmful to the environment, aligning their business into more environmentally sustainable trajectories (Hegeman & Sørheim, 2021). In other cases, these investments may also be a way of deciding which technologies will likely reach consumers and controlling the pace of development of these technologies (Béné, 2022).

We have two examples to illustrate this group of strategies. The first is that meat, veterinary and seafood companies are massively investing in plant-based and cellular agriculture technologies, which aim to hack traditional meat production systems. For instance, three leading players in the beef packing industry, such as Tyson Foods, Cargill, and BRF, are among the main investors in alternative protein companies like UPSIDE Foods, Aleph Farms, Myco Technologies, and Believer Meats. Similarly, Nutreco, one of the leading companies in animal nutrition, has invested in startups such as MosaMeat, Enough, and BlueNalu. A second example is traditional players in the synthetic ag-input industry investing in biological inputs. Given the current status of the technology, it is not yet clear that biological inputs will completely replace synthetic inputs in the future. It is more reasonable to think that bio-based inputs will coexist with synthetic inputs in farmers' production functions (Goulet & Hubert, 2020). However, biological inputs bring a new way of targeting farmers' operations that challenges years of development of the traditional ag-input sector based on standardization and massification, requiring more customized approaches considering soil and climate characteristics. As examples, we have Bayer investing in Joyn Bio, BASF in Provivi and Groundwork or Sumimoto in TerraMera, among many others.

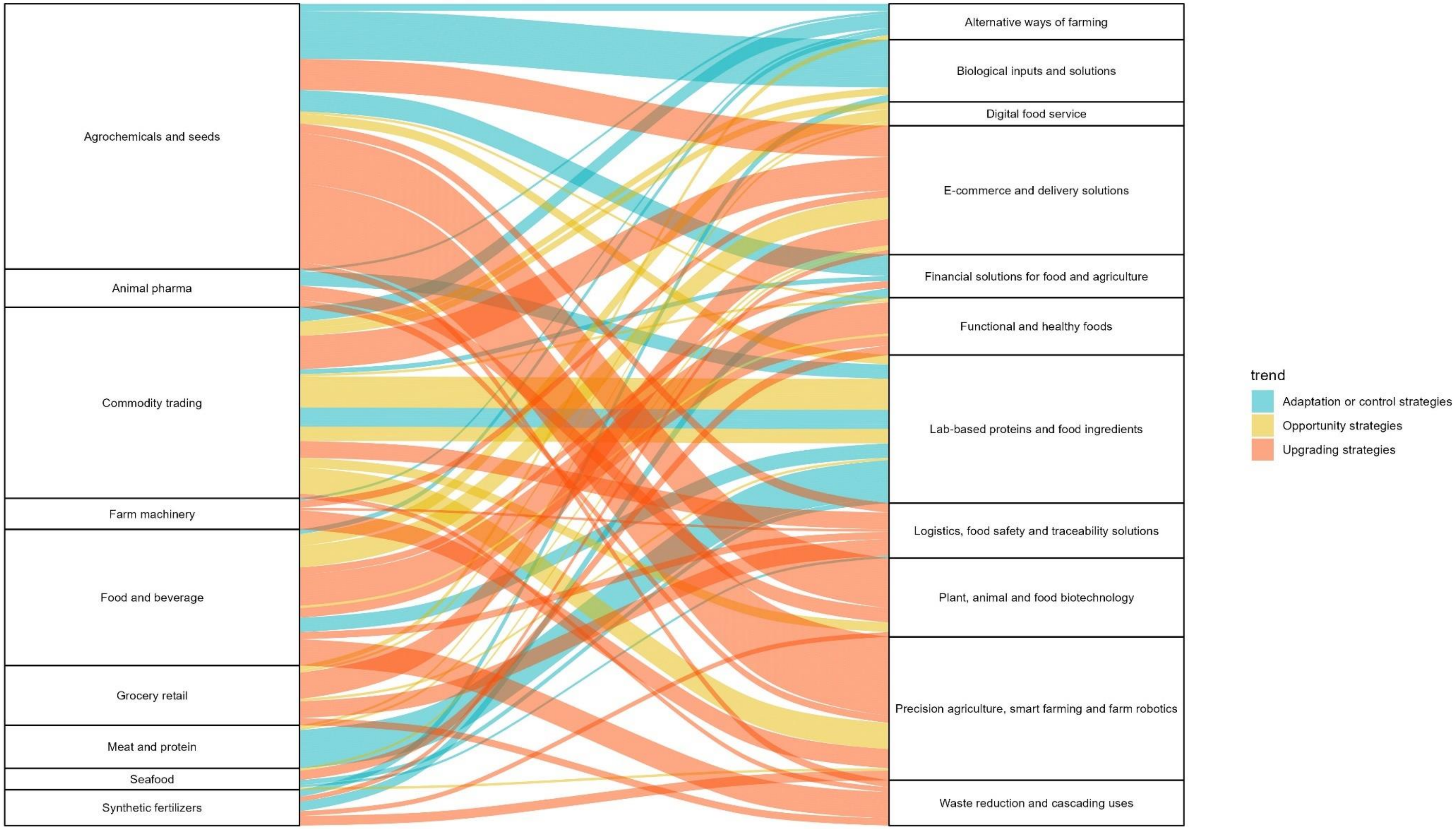

Figure 2.7. Three trends of investments by dominant firms: upgrading strategies, adaptation or control strategies, and opportunity strategies.

Opportunity strategies. These are investments toward indirectly related sectors (or even entirely unrelated). We call them opportunity strategies since incumbents decide to invest in these companies foreseeing they will have a dynamic development in the future, but are not explicitly related to their core business. They are seizing opportunities to increase their strategic portfolio's revenue without necessarily looking to incorporate any of these technologies into their operations. For example, commodity trading companies have been considerably active in investing in different businesses such as cellular agriculture and plant-based, biological inputs or precision agriculture, which are only indirectly related to their core operation in agri-food value chains (e.g., Bunge in PivotBio, MycoTechnologies or Seedcorp, LDC in Motif, Gathered Foods and ADM in Believer Meats and New Culture). Something similar happens with retail grocery companies investing in controlled environment agriculture or food and beverage companies investing in digital food service.

2.6 Conclusions

Technological change promises to improve agri-food GVCs in front of the multiple environmental and social challenges ahead. Novel products and processes are transforming food production, processing, and distribution. This chapter first presented a comprehensive overview of the innovation landscape in different stages of agri-food GVCs, from farming inputs to last-mile delivery. Then, we analyzed the role of large multinational companies dominating AFS, exploring the corporate venture capital strategies they follow to be on board with this technology-driven transformation.

Young emergent companies are more flexible and can be more dynamic regarding innovation. Startup ecosystems are bringing several solutions to transform food systems. However, it is hard for these companies to cover successfully every step from scientific discovery to markets. The risks involved in R&D, the financial requirements to manufacture and commercialize new products, and the challenge regarding distribution channels and market intelligence may likely give a relevant role to incumbent firms in the long run. From a Shumpeterian perspective, innovation in agri-food GVCs is happening at two levels: small firms and entrepreneurs propose new solutions at the discovery level, whereas big firms are needed to upscale these innovations and carry them to massive markets. Thus, technological change does not necessarily imply more inclusive governance of AFS.

This chapter showed that incumbent agri-food companies follow different strategies for investing in smaller firms in AFS. Unfortunately, we do not have enough evidence to make conclusive statements about the underlying reasons for these corporate strategies. In some cases, the investing interest of incumbent firms may be to secure access to these technologies once they are commercially available. In other cases, these investments may be defensive to slow down the development of these technologies and ensure their leading positions. Finally, part of these investments could be a corporate response to rising social claims about the environmental sustainability of their operations. Nevertheless, despite the reasons that drive these investments, it is evident that large multinational firms are looking at new technologies developed by smaller and technologically more dynamic firms.

Our research has implications for policymakers and business managers. From a policy perspective, the first point to consider is that although substantial investments in technology are needed to reduce environmental impacts and improve diets, there are also risks involved in this process. The displacement of the smallest actors, technology accessibility for consumers, and uneven distribution of innovation rents between world regions are issues in a technological transition, especially in a context in which corporate influence may create institutional lock-ins that lead to replicating many of the current problems in food value chains. Technological innovation must be coupled with several changes at the policy level to mitigate the potential risks for social sustainability brought by new technologies (C. B. Barrett et al., 2020; Moberg et al., 2021). Policies that promote competition and mitigate excessive market power must be part of the policy agenda.

A second point from a policy perspective is that stewardship strategies are needed to stimulate technologies with promising environmental or social sustainability potential, especially during the initial stages. Venture capital is necessary for innovation, but investors may be risk-averse and seek the low-hanging fruit that provides fast and attractive returns. As we saw in our analysis, most of the innovation efforts and funds are channeled toward the downstream segment of the value chain (e.g., e-commerce solutions, in which technologies are more mature and have more profit potential). As such, many initiatives with a strong GHG mitigation potential upstream in the value chain (e.g., digital farming, crop biotechnology, or alternative proteins) receive less attention since they present more technical and commercial risks and require a longer timeframe to show investment returns. In this sense, the idea of a mission-oriented approach toward innovation makes sense, with a problem-solving focus and articulation between the public and private sectors to favor the crowding in from private funds (Dosi et al., 2023; Mazzucato, 2021).

Regarding business implications, our study presents a complete landscape of what is happening in the entrepreneurial world in AFS. This is essential to understanding the direction of technology investments and identifying innovation gaps. While many small and medium technological firms are leading the transition toward more sustainable food systems, incumbent firms seem to play a critical for the transition from lab to market. The more disruptive a technology is, the more challenges developers face regarding organizational capabilities, technical skills, and value chain building (Reis et al., 2020). Small venture capital investors, such as seed funds, startup accelerators, science venture funds, and government agencies, play a critical role when looking at the problem from a network perspective. These actors create innovation ecosystems by placing smaller investments in many companies, which leads to sharing information and lessons from the entrepreneurial experience. In the long run, this is critical to accelerating innovation while minimizing failure rates among young firms (Kulkov et al., 2020).

This chapter is a first approximation to describing the changing socio-technical regime in agri-food value chains. The main contribution of our work is to introduce an industrial organization perspective to the food value chain literature in the context of technological change. Despite presenting a comprehensive map of the landscape of innovations and explaining the role of incumbents, we do not show specific measures regarding changing concentration or market power rates in AFS. Given the novelty of the problem we are studying, we present some lines of thought regarding the role of corporate venture capital without providing an impact assessment. Moreover, this chapter does not address the potential consequences of industrial concentration on farmers and consumers. Both farmers and consumers are the weakest actors in the value chain but also the critical ones in adopting many of the technologies we have discussed in this chapter. Without massive adoption, technologies such as biological inputs, new seed traits, lab-based proteins, sustainable packaging, or automated delivery, among many others, will not create neither economic nor environmental impact. Further research should seek to provide empirical evidence on how the role of incumbent firms may foster or hinder the market reach of these technologies and whether there are welfare impacts in terms of prices and accessibility for farmers and consumers.

Chapter 3 Institutional and macroeconomic stability mediate the effect of auctions on renewable energy capacity

Abstract: Renewable energy (RE) auctions have become an increasingly popular policy instrument for decarbonizing the global energy matrix, and have been rapidly adopted by several countries worldwide. Previous research has used data from higher-income countries and TWFE models to estimate the impact of auctions on RE capacity, mostly with favorable results. However, these studies did not account for heterogeneous treatment effects across units to explore whether auctions are also effective in countries with unstable business environments. We analyze whether auctions also foster RE in countries experiencing macroeconomic instability or poor institutional quality. For this purpose, this study has drawn from multiple publicly available databases to build a dataset comprising 98 countries from 2000 to 2020. Our definition of RE includes solar, wind, and biomass sources. We first cluster countries by the quality of their business environment and then perform a differences-in-differences analysis considering staggered treatment adoption. We find that auctions positively affect RE capacity, yet the average treatment effects are higher for countries with better business environments. Thus, governments should exercise caution in adopting this instrument, especially in countries that experience macroeconomic or institutional instability. At the same time, dynamic treatment effects suggest that the policy needs time to show results.

Keywords: renewable energy, auctions, policy evaluation, difference-in-differences, causal inference

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3.1 Introduction

Energy systems account for the largest share of global anthropogenic GHG emissions (Lamb et al., 2021). Approximately 70% of those energy-related emissions come from electricity and heat production to supply energy to industries and private housing (Dhakal et al., 2022). Thus, the rapid economic growth in low and middle-income countries is expected to increase their energy-related GHG emissions (Henriques & Borowiecki, 2017). Therefore, low-carbon electricity systems predominantly based on renewables must keep temperatures 1.5 degrees below preindustrial levels (IPCC, 2022).

Many countries worldwide are decarbonizing their energy matrixes through RE sources. This transition toward low-carbon energy systems has been supported by policies aiming to create an enabling environment for investments in this type of technology (Jordan & Huitema, 2014). RE auctions are examples of the institutional innovation being used to promote renewables. This policy has become increasingly popular recently, gradually replacing administratively established incentives, such as feed-in tariffs and RE tradable green certificates (Fitch-Roy et al., 2019; Grashof, 2021). RE auctions synthesize elements from price-based and quantity-based policies, ensuring fair remuneration for RE projects while avoiding excessive support costs (IRENA & CEM, 2015). Consequently, even low and middle-income countries without a track record in RE policies have adopted RE auctions (IRENA, 2019; Viscidi & Yepez, 2019).

A growing body of literature analyzes the effects of various policies on the deployment of RE (Bento et al., 2020; Bersalli et al., 2020; Jenner et al., 2013; Kersey et al., 2021; Kilinc-Ata, 2016; Liu et al., 2021; Romano et al., 2017). Although the evidence on auctions is still thin, several studies suggest they are an effective policy instrument (Bento et al., 2020; Bersalli et al., 2020; Jenner et al., 2013; Kilinc-Ata, 2016). Most of these studies, however, primarily focus on stable OECD or European economies. Despite the global optimism surrounding auctions and their rapid adoption, whether they are an appropriate instrument for all countries remains an open question. Furthermore, RE projects tend to be capital intensive (Mazzucato & Semieniuk, 2018) and involve lengthy and somewhat uncertain payback periods; these economic and political risks can undermine investors' willingness to fund RE (Gatzert & Vogl, 2016). This is especially relevant for many low-income countries, where the business environment is usually affected by devaluation, inflation, sovereign debt crises, a weak rule of law, ineffective contract enforcement, and political volatility. Evaluating auctions in such contexts is relevant because most of the renewable potential is in low- and middle-income countries, where we expect electricity demand to rise (Vanegas Cantarero, 2020).

We build on this body of literature by analyzing whether the impact of RE auctions varies according to the quality of the business environment in countries that have adopted RE auctions. The business environment comprises macroeconomic stability and institutional quality. Drawing from multiple publicly available databases, we have constructed a panel dataset for the 2000–2020 period, covering 98 countries with distinct macroeconomic and institutional profiles. In particular, we address the following research questions: 1) Do RE auctions affect the deployment of RE in contexts of macroeconomic instability and poor institutional quality? and 2) Does the effectiveness of auctions in promoting investments in RE vary across different technologies (i.e., solar, wind, and biomass)?

To our knowledge, this is the first quantitative study that uses data from many countries with varying macroeconomic and institutional conditions to analyze the effects of RE auctions in different business environments. Furthermore, we make an empirical contribution using two novel differences-in-differences (DiD) estimators for staggered treatment adoption (Callaway & Sant'Anna, 2021; Gardner, 2021), which allows us to account for heterogeneous treatment effects and differential timing and compare these results with those of the more traditional TWFE approach.

The remainder of this chapter is structured as follows: Section 3.2 describes the conceptual nexus between auctions, RE capacity, and how the quality of the business environment may affect, theoretically, the efficiency of this policy instrument. Section 3.3 describes the primary data sources, and Section 3.4 details the empirical strategy used in the chapter. Section 3.5 shows the results of our empirical analysis, which are then discussed in Section 3.6. The final section presents policy implications and further research opportunities.

3.2 Auctions, renewable capacity, and the business environment

In RE auctions, the government calls for tenders to procure a certain amount of RE capacity, RE generation, or a fixed total budget, and companies compete to supply those volumes. Although a growing body of literature has recently analyzed the efficiency of different policies to foster RE capacity, empirical evidence on auctions is still scarce. Jenner et al. (2013) studied the effect of several RE policies from 1992 to 2008 for 26 European countries. The authors found mixed results, in which tendering schemes have positive results in interaction with feed-in tariffs for wind but not for solar capacity. Kilinc-Ata (2016) studied 27 EU countries and 50 U.S. states from 1990 to 2008 and found a positive but modest impact of auctions over the share of RE capacity. A similar result was found by Bento et al. (2020) for 20 OECD economies in the period 2004–2014, showing that the implementation of auctions results in higher investments in RE for the period but emphasizing that the implementation conditions are essential for these mechanisms to work (the illustrate this using Italy as an example, where there was a downturn in the investments after the first policy change).

The previous results were found largely in developed economies, whose macroeconomic variables and institutional conditions are normally more stable. Studies focusing on lower and middle-income countries often research a few case studies and use qualitative assessments. For example, Winkler et al. (2018) and Bayer et al. (2018) used six and four country cases, respectively, and neither of them is conclusive regarding the effectiveness of tendering mechanisms. Studies that focused on particular countries, such as Brazil (Bayer, 2018), South Africa (Kitzing et al., 2022), and India (Shrimali et al., 2016), also showed inconclusive results regarding the effects of auctions. To the best of our knowledge, only two papers include a quantitative assessment of auctions in a more comprehensive study design, including not only OECD or European countries but also low and middle-income countries. Hille and Oelker (2023) included a sample of 189 countries for 2005–2018 and found a positive impact of tendering schemes over solar and wind installed capacity. Bersalli et al. (2020) included a set of 30 European and 20 Latin American countries and found that auctions positively affect the yearly rate of RE added capacity. **Appendix 3 *1*** presents a more detailed synopsis of the literature review.

Even when some of the presented papers include a more comprehensive sample of countries, none specifically addresses the role of institutional and macroeconomic aspects on the efficiency of auctions over the rate of RE capacity. This question is relevant, however, considering that auctions have become a popular policy instrument in recent years. According to the IEA (2021), the volume of RE capacity auctioned has quadrupled between 2015 and 2020. By 2020, 116 countries had held auctions at least once (REN 21, 2021, p. 40). Most recent newcomers to auctions are countries in Asia, South

America, and Sub-Saharan Africa, which usually face macroeconomic instability and lower institutional quality compared with OECD or European countries. Can auctions perform well in countries with unstable business environments despite their rapid adoption? Authors who have explored the role of institutional quality over the deployment of RE in the energy matrix (Cadoret & Padovano, 2016; Sequeira & Santos, 2018; Uzar, 2020) have proposed that democratization and good institutional quality have a positive impact in the long run on RE investments. However, this chapter is concerned with how the quality of the business environment may condition the efficiency of RE auctions to promote RE capacity.

Some features of auctions make them a suitable instrument to promote RE in countries with weak business environments. The first element is the reduction of information asymmetries between energy buyers and sellers (IRENA & CEM, 2015). The government only partially knows the actual marginal costs of the energy produced, leading to a potential overcompensation of costs (especially for mature technologies). Auctions promote competition and encourage price discovery, reducing public expenses to remunerate RE (Barnea et al., 2022; Polzin et al., 2019). Tendering schemes also allow better control of the volumes provided (del Río, 2017). Therefore, countries with limited public budgets might benefit from auctions, which are cost effective for procuring RE. A second argument relates to risk mitigation for the government and private investors. Auction winners sign a legally binding agreement (usually a long-term contract) that specifies the quantity to supply and the price received. This provides more robust warranties to investors against sudden policy changes (IRENA, 2017). Polzin et al. (2019) proposed that auctions effectively reduce risks and contribute to attracting early-stage capital. Enforcement issues, potential penalties, and conflict settlement are more evident within this legal framework. Moreover, auctions can be designed to provide clear-cut safeguards against inflation or devaluation (Viscidi & Yepez, 2019). From the policymaker's side, financial or physical prequalifications usually improve the instrument's effectiveness (Matthäus, 2020).

However, depending on the macroeconomic and institutional settings in which auctions are held, they could be less effective in deploying RE or may even lead to undesirable outcomes. The first critique relates to noncompetitive locations or small markets where competition is not guaranteed. While auctions could be tailored to promote competition in contexts of high market concentration, the risk of collusion typically reduces its efficiency (Compte et al., 2005). In the last two decades, many developing countries have introduced reforms to their electricity markets, such as dismantling public monopolies, unbundling production and distribution, and fostering the entry of international power producers. However, these reforms have had varying success rates; they have not always intensified competition or reduced electricity prices (Nagayama, 2007; Zhang et al., 2008).

A second critique relates to transaction costs (del Río & Linares, 2014). Hidden transaction costs may undermine the savings for governments while restricting the chance to bid to big firms (which are those most likely to undertake the administrative burden of the process). While this is a general problem of auctions as a policy instrument, weak institutional settings may amplify transaction costs (North, 1987). The third potential disadvantage comes from the high levels of corruption and an overall lack of trust in the government. The literature on public procurement systems indicates that lower quality tends to be observed in the procured goods or contracted infrastructure in contexts with high levels of corruption (Dastidar & Mukherjee, 2014). Furthermore, high levels of corruption can lead to overpricing (Arozamena & Weinschelbaum, 2009; Finocchiaro Castro et al., 2014). The final critique relates to underbidding and the winner's course. Competitive pressures might force bidders to offer prices that barely cover marginal costs, which may be particularly relevant to many bidders (Hong & Shum, 2002). In such contexts, sudden exchange or interest rate alterations in unstable environments can severely affect bidders' projected revenues, leading to early project desertion (Bose

& Sarkar, 2019). The failure to build the infrastructure can be an issue even in auction programs with high realization rates.

As presented in this section, even when there are favorable results of auctions over total RE investments, it is still unclear from a theoretical and empirical standpoint whether auctions are an effective instrument for fostering RE capacity in countries with unstable business environments. Despite the instrument's popularity and the increasing number of adopters from low and middle-income countries, given the arguments presented in this section, auctions will not necessarily contribute to deploying RE capacity in such institutional and macroeconomic contexts. This is what this chapter will explore. The following two sections present the data and methods used for this purpose.

3.3 Data and descriptive statistics

We built a database with information from publicly available data sources for 98 countries. Of these, 70 implemented auctions between 2000 and 2020. We compiled data from 98 countries on their RE energy policies and installed capacity, socioeconomic characteristics, natural endowment, and business environment for this period.[22] ***Table 3.1*** presents descriptive statistics, definitions, and sources for each variable used in the analysis.

We used multiple sources to code information for auctions, our treatment variable (we explain this further in subsection 3.4.a). This includes reports and databases from the AURES II project, the International Renewable Energy Agency (IRENA), the Inter-American Development Bank (IADB), and previous papers (del Río & Kiefer, 2021; Kruger et al., 2018; Matthäus, 2020). We also coded information for feed-in policies (tariffs and premiums). We control for feed-in policies because they are the most popular and widely adopted type of policy (Ferroukhi et al., 2018, p. 22), and it is the policy most gradually being replaced by auctions (REN 21, 2021, p. 79). For our outcome variable, we collected information from the IRENA on the capacity of solar, wind, and biomass technologies, which is expressed as a share of the total installed capacity (explained in detail in subsection 3.4.a).

Our empirical analyses control for variables that characterize the countries' socioeconomic profiles and natural endowment. First, we use gross domestic product (GDP) per capita from the World Bank to capture economic growth and overall income level. We use World Bank and Ember's Global Electricity Review data to capture countries' dependency on fossil fuels and energy imports. For this purpose, we use variables representing oil rents, carbon dioxide (CO_2) emissions per capita, the share of electricity produced through fossil sources, and net electricity imports. Finally, given that the adoption of RE depends on the natural resources available, we use data from the Global Solar Atlas and the Global Wind Atlas by the World Bank to control for solar potential and wind speed and data from United Nations on forest biomass stock as a proxy for biomass potential.

Previous studies on auctions included covariates related to the level of development (i.e., GDP or income) and political status (i.e., type of political system or the strength of the fossil lobby). Nevertheless, this study aims to comprehensively address the quality of the business environment, defined as a combination of macroeconomic stability and institutional quality factors. Macrolevel stability is based on the four points established by the Maastricht convergence criteria: price stability, sustainable public finances, exchange rate stability, and long-term interest rates (European Central

[22] Because some variables have missing information for 2020, most of the analysis are run considering a fully balanced panel for the period 2000–2019.

Bank, 2020). We use the variable inflation from the International Monetary Fund (IMF) for price stability. We also include dummy debt and currency crisis variables to reflect sustainable public finances and exchange rate stability. These data come from Laeven and Valencia (2020) and Nguyen et al. (2021). Additionally, the IMF financial development index is used as a proxy for the long-term quality of the financial system. For institutional quality, we use the six composite indicators reported in the Worldwide Governance Indicators (GWI) database, published by the World Bank (Kaufmann et al., 2010).

Table 3.1. Description of the variables used in this study

Variable	n	min	max	median	mean	std.dev	Period Available	Unit	Description	Source
Number of years with auctions	2058	0	18.0	4.0	4.5	4.4	Time invariant	Count	Total number of years since the first auction up to 2020.	See supplementary material
Auctions	2058	0	1.0	0	0.2	0.4	2000–2020	Dummy	AUC3 = 1 if treatment is in place; AUC3 = 0 otherwise	See supplementary material
Feed-in policies	2058	0	1.0	0	0.4	0.5	2000–2020	Dummy	FIT = 1 if feed-in-policies (tariffs or premiums) are in place for a country in a specific year; FIT = 0 otherwise.	Global Data Pack 2021 (REN 21) and complementary sources
Share of wind, solar and biomass	2058	0	62.0	2.5	6.5	9.2	2000–2020	%	Participation of wind, solar and biomass capacity over total system capacity in a specific year	IRENA
Share of wind	2058	0	40.8	0.1	2.8	5.5	2000–2020	%	Participation of wind capacity over total system capacity in a specific year	IRENA
Share of solar	2058	0	23.8	0.1	1.6	3.7	2000–2020	%	Participation of solar capacity over total system capacity in a specific year	IRENA
Share of biomass	2058	0	26.8	0.7	2.1	3.4	2000–2020	%	Participation of biomass capacity over total system capacity in a specific year	IRENA
GDP per cápita in 2015 dollar (4)	2058	259	112,373	7,828	16,757	20,073	2000–2020	Constant 2015 USD	GDP per capita	World Bank
Oil rents	1960	0	58.2	0	3.2	8.5	2000–2019	% of GDP	Difference between the value of crude oil production at regional prices and total costs of production.	World Bank
Net imports of electricity	2058	−77.0	66.7	0	-0.2	12.2	2000–2020	TW	Net imports of electricity from all sources	EMBER
CO2 emissions per cápita (4)	2058	0.1	67.0	4.4	6.4	7.2	2000–2020	Tonnes per person	CO2 emissions per capita	OWiD
Share of electricity from fossil sources	2058	0	100.0	62.5	58.7	32.6	2000–2020	% of total electricity generation	Share of electricity generation from coal, oil and gas sources combined	OWiD
Solar potential (1)	2058	2.0	6.4	4.8	4.6	1.1	Time invariant	kWh/m2/day	Solar theoretical potential, measured by Global Horizontal Irradiation Index (GHI, country median, long-term)	Solargis - World Bank
Wind potential (1)	2058	3.3	9.9	6.5	6.5	1.3	Time invariant	meters/second	Mean wind speed at height 100 m (for 50% windiest areas)	Global Wind Atlas
Biomass potential (1)	2058	0	289.3	99.7	107.1	59.9	Time invariant	tonnes/hectare	Above-ground biomass stock in forest in year 2010	United Nations
FDI (2)	1960	3.5	100.0	35.2	39.7	23.4	2000–2019	Index (0–100)	Financial development index that measures depht, access and efficiency of financial institutions and financial markets	IMF
Inflation	2058	−8.2	168.6	3.3	5.0	7.5	2000–2020	%	Annual average of monthly rates of inflation for a specific year	IMF
Currency crisis	1960	0	1.0	0	0	0.2	2000–2019	Dummy	currency_crisis = 1 if the country experienced a currency crisis in the specific year; currency_crisis = 0 otherwise	Laeven & Valencia (2020) and Nguyen (2021)
Debt crisis	1960	0	1.0	0	0.1	0.3	2000–2019	Dummy	debt_crisis = 1 if the country experienced a currency crisis in the specific year; debt_crisis = 0 otherwise	Laeven & Valencia (2020) and Nguyen (2021)
Regulatory quality (rqe) (3)	2058	0	100.0	52.2	54.6	21.6	2000–2020	Index (0–100)	Ability of the government to formulate and implement sound policies and regulations	WGI Database (World Bank)
Rule of law (rle) (3)	2058	0	100.0	42.4	47.7	25.7	2000–2020	Index (0–100)	Quality of contract enforcement, property rights, the police, and the courts	WGI Database (World Bank)
Government effectiveness (gee) (3)	2058	0	100.0	40.1	45.2	23.9	2000–2020	Index (0–100)	Quality of public and civil services and the quality of policy formulation and implementation	WGI Database (World Bank)
Control of corruption (cce) (3)	2058	0	100.0	36.0	43.2	24.8	2000–2020	Index (0–100)	Extent to which public power is exercised for private gain	WGI Database (World Bank)
Political stability and no violence (pve) (3)	2058	0	100.0	59.1	58.5	20.6	2000–2020	Index (0–100)	Likelihood that the government will be destabilized or overthrown by unconstitutional or violent means	WGI Database (World Bank)
Voice and accountability (vae) (3)	2058	0	100.0	56.4	57.0	24.5	2000–2020	Index (0–100)	Freedom to select government, freedom of expression, freedom of association and free media	WGI Database (World Bank)

(1) Complementary sources were used in case of missing data.

(2) The original index goes from 0 to 1, but it was rescaled from 0–100 to facilitiate the interpretation of the coefficient.

(3) The original index goes from −2.5 to 2.5, but it was rescaled from 0–100 to facilitiate the interpretation of the coefficient.

(4) For estimation purposes, these variables are included in its log form.

3.4 Empirical Strategy

The chapter aims to determine whether RE auctions are an effective mechanism for promoting investments in RE capacity in unstable business environments. For that purpose, we adopt a causal inference analysis to establish the links between adopting auctions (considered the treatment) and the changes in the share of RE capacity (the outcome), subsetting the countries according to the quality of their business environment. Given the nature of our problem, we cannot assign the treatment randomly to avoid self-selection. Under randomized designs, the adoption of the treatment is independent of the attributes of the individuals; thus, it is possible to ensure that the final observed effect is a direct consequence of the treatment. However, this is not an applicable method for policy choices at the country level. In this study, we work with observational data and use quasiexperimental techniques to establish causality.

Many of the quantitative studies presented in Section 3.2 relied on TWFE models to evaluate the effects of RE policies (see **Appendix 3** ***1*** for a detailed summary of the methods used by previous papers). Nevertheless, TWFE regression provides biased estimations under differential timing in adoption with heterogeneous treatment effects (Borusyak et al., 2021; Goodman-Bacon, 2021). This is relevant to our case because, as countries have adopted auctions at different points in time, it is unlikely that the policy outcomes are perfectly homogeneous across all countries in the sample. Therefore, we applied DiD techniques, one of the most common quasi-experimental methods used in Economics. Furthermore, we also considered that not every country adopts the policy (i.e., the treatment) simultaneously.

In particular, our empirical strategy comprises four steps:

1. *Definition of the treatment and outcome variables:* The two most important variables in our setting are the definition of the treatment (in this case, auctions) and the outcome (the result we are evaluating). This is explained in subsection 3.4.a.
2. *Identifying the determinants of RE auction adoption:* We start our empirical analyses by checking to what extent self-selection might be a concern, emphasizing whether countries with specific institutional or macroeconomic features are more likely to adopt auctions. This is presented in subsection 3.4.b.
3. *Subsampling according to the business environment:* Given the purpose of this study, we need to incorporate the quality of the business environment in the analysis. Therefore, we apply Principal Component Analysis (PCA) and Cluster Analysis to reduce the dimensionality of the data and create subgroups for our research. This is detailed in subsection 3.4.c.
4. *Calculation of average treatment effects on the treated:* Taking as inputs the results from steps 1 to 3, we calculate the average treatment effect on the treated (i.e., the impact of adopting auctions on the share of RE capacity for the countries in the sample). This is the primary goal of our analysis. A detailed explanation of the methods used is provided in subsection 3.4.d.

A summary of the methodology presented in this section is shown in ***Figure 3.1***.

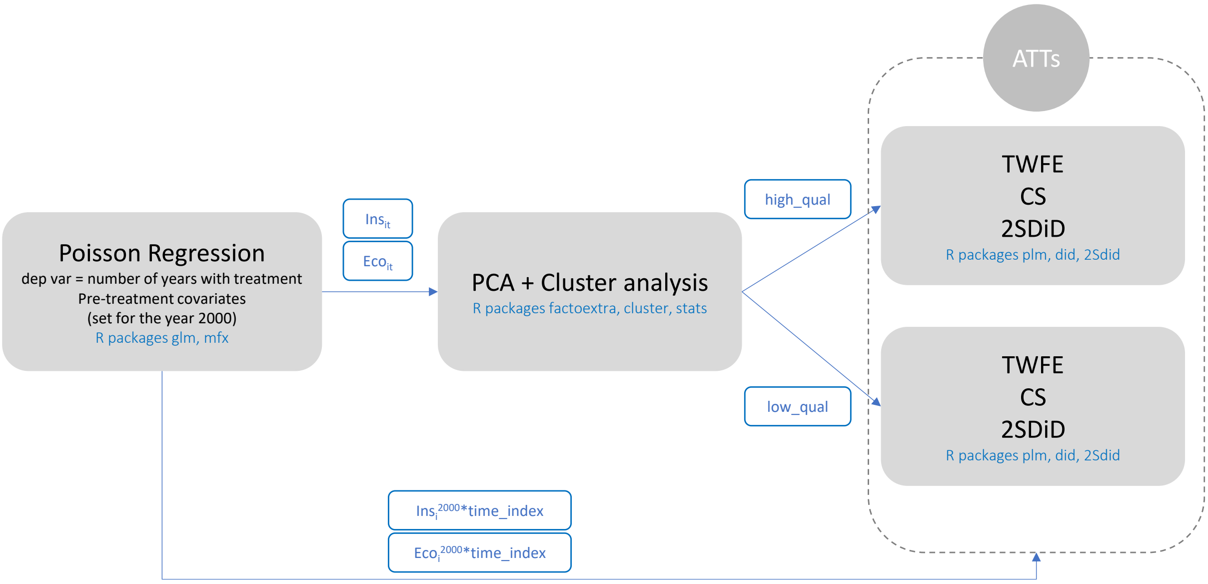

Figure 3.1. Summary of the methodology.
We use Poisson regression to explain the influence of institutional (Ins_{it}) and macroeconomic (Eco_{it}) variables in adopting auctions. Then, we use both sets of variables (Ins_{it} and Eco_{it}) to classify countries according to the quality of their business environment. Finally, we calculate the average treatment effects of adopting auctions using three estimators (TWFE, CS, and DiD), disaggregating the analysis by the quality of the business environment.

a. Definition of the treatment and outcome variables

There are different alternative measures for the incidence of renewable sources in the energy matrix (**Appendix 3 *1***). In this chapter, we define the outcome variable in terms of capacity, i.e., the share of solar, wind, and biomass capacity over total installed capacity in the electricity system for country i in time t:

$$y_{it} = \frac{CapacitySolar_{it} + CapacityWind_{it} + CapacityBiomass_{it}}{Total\ System\ Installed\ Capacity\ (RE\ and\ non\ RE)_{it}} \tag{3.1}$$

We use electricity capacity rather than electricity generation because capacity more accurately reflects the long-term direction of the electricity system and is less dependent on short-term determinants (i.e., climate, fluctuation in fossil costs or short-term policy preferences). We include wind and solar energy because these are the two most widely adopted RE sources. We also incorporate biomass, given its role in providing stable capacity to the system. However, we exclude hydropower sources due to reported negative environmental impacts (D. M. Rosenberg et al., 2000). We also use individual measures for the share of solar, wind, and biomass as outcome variables.

As for the treatment variable, we consider the adoption of auctions for empirical purposes. In other words, countries that have implemented auctions between 2000 and 2020 are considered “treated,” and countries that have not implemented auctions during this period are considered “controls” (regardless of any other RE policies or incentives they may have). We define the treatment as binary (1 if the country has adopted auctions; 0 otherwise) and irreversible (once the country has implemented auctions for the first time, it stays treated up to the end). Even if a country does not regularly run auctions every year, implementing an auction scheme has a double effect: first, it helps to create a lasting legal and institutional framework that leaves a scarring effect on the system; and second, it sends a signal to investors regarding the willingness of the authorities to promote RE (IRENA

& CEM, 2015; Maurer & Barroso, 2011). **Appendix 3 *2*** details each country's treatment start and the sources used to code this variable.

In our sample, 70 of the 98 countries implemented auctions between 2000 and 2020 (i.e., "treated"), whereas 28 did not (i.e., "controls")[23]. ***Figure 3.2*** shows which countries are treated and which are controls.

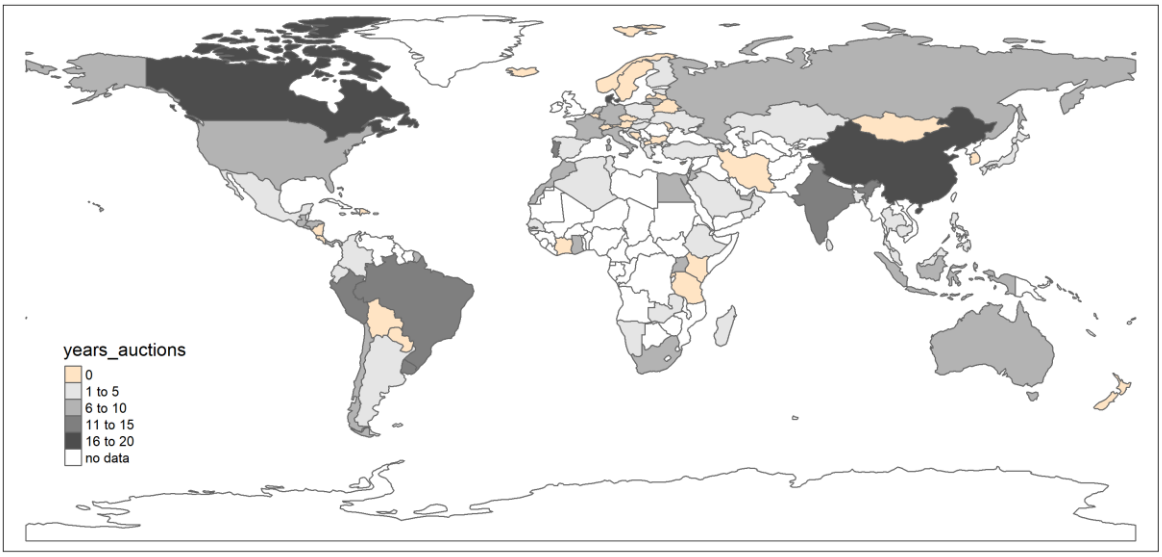

Figure 3.2. Countries selected in the sample and length of the treatment.

b. Identifying the determinants of RE auction adoption

Because self-selection into treatment might be a concern, we test whether countries with specific institutional or macroeconomic features are more likely to adopt auctions. For this purpose, we follow an approach similar to Hoynes and Schanzenbach (2009). We run a regression in which we take as the dependent variable the number of years a country has been applying auctions (a proxy variable to explain the timing of adoption). ***Figure 3.2*** shows the length of the treatment for the treated units. We use a Poisson model, which is a regression model suitable for count data, of the following form:

$$z_i^{2020} = REN_i^{2000}\beta + ENE_i^{2000}\gamma + ECO_i^{2000}\rho + NAT_i\delta + INS_i^{2000}\theta + \varepsilon_i \qquad (3.2)$$

z_i^{2020} is a count variable that reflects the number of years since country i implemented its first auction. The variable takes the value 0 for nonadopters. We regress this on pretreatment variables to identify what characteristics help explain if and when countries choose to adopt auctions. Because some of our independent variables (e.g. those related to the profile of the energy matrix in a country) could simultaneously affect and be affected by auctions, all our explanatory variables represent the status of countries in the year 2000 (indicated by the superscript), when none of the countries in our dataset had implemented auctions yet. The choice of explanatory variables in this analysis was informed by the scientific literature and technical reports that explain why countries adopt auctions as a policy instrument to foster RE. These include the following variables described in Equation 2:

[23] Originally, we collected data for 100 countries. However, the UK and Ireland were excluded from the analysis because both countries had RE auctions programs during the 1990s, before the start date of our analysis.

REN_i^{2000} is a vector of variables reflecting the status of the renewable sector in the year 2000, including the percentage of RE capacity (Marques and Fuinhas, 2012) and if it already had feed-in policies in force at that time (Aguirre and Ibikunle, 2014; Bersalli et al., 2020; Kilinc-Ata, 2016; Romano et al., 2017; Zhao et al., 2013). ENE_i^{2000} is a group of variables reflecting the profile of the energy matrix in the year 2000. We include oil rents (Sequeira and Santos, 2018), the share of electricity generation from fossil fuels (Aguirre and Ibikunle, 2014; Marques and Fuinhas, 2012), emissions per capita (Bersalli et al., 2020; Cadoret and Padovano, 2016; Uzar et al., 2020), and net electricity imports (Bersalli et al., 2020; Jenner et al., 2013; Romano et al., 2017). NAT_i includes variables that capture the natural endowment of the country (Aguirre and Ibikunle, 2014). These variables are time-invariant, so the superscript "2000" is not included. ECO_i^{2000} is a vector of variables related to the macrolevel instability in 2000 and INS_i^{2000} is a vector of variables that describe institutional quality in 2000. ε_i is the error term, which we cluster using the World Bank income groups in the year 2000. We use the R package *mfx* for calculation purposes, which allows us to recover marginal effects and calculate clustered standard errors (Fernihough & Henningsen, 2019).

Table 3.2 summarizes the estimation results for equation (1), considering only the best-performing model. These results are robust to different model specifications, as presented in **Appendix 3** ***3***. All results are expressed in average marginal effects, meaning they reflect the predicted change in the dependent variable (number of years from the first auction up to 2020) from a unit change in the explanatory variables. For macroeconomic variables, financial development index (FDI) and inflation consistently have significant coefficients across all model specifications. The positive sign for FDI indicates that a more developed financial infrastructure lowers the cost of capital to fund RE projects. However, considering how unpredictable costs and income become in inflationary contexts, a negative sign for inflation is expected. In terms of the institutional setting, the rule of law is significant. According to Kaufmann et al. (2010, p. 4), the rule of law indicates "the respect of citizens and the state for the institutions that govern economic and social interactions among them." The negative sign in this case is contrary to intuition. The first possible explanation for the negative sign is that the level of regulation might operate negatively in the mind of investors if they foresee over-regulation (Sisodia et al., 2016). A second explanation is that in highly corrupted countries, auctions may help reduce functionaries' discretion in handling procurement projects (Baldi et al., 2016).

Table 3.2. Addressing self-selection with a Poisson model

Dep. Var.: Lenght of treatment (number of years with auctions in the period 2000–2020)	
Share of wind, solar and biomass	0.228***
	(0.068)
Feed-in policies	1.889
	(1.701)
share fo electricity from fossil sources	−0.016
	(0.015)
Oil rents	−0.081***
	(0.026)
CO2 emissions per capita	0.471
	(0.296)
Net imports of electricity	−0.011
	(0.044)
Solar potential	1.225***
	(0.350)
Wind potential	0.460*
	(0.235)
Biomass potential	−0.005**
	(0.002)
FDI	0.104***
	(0.016)
Inflation	−0.070***
	(0.023)
Currency crisis	6.467*
	(3.914)
Debt crisis	−0.334
	(1.943)
Rule of law	−0.093***
	(0.025)
Num. obs.	98
Deviance	350.49
AIC	626.03

***p < 0.01; **p < 0.05; *p < 0.1
(Standard errors)
Errors clustered by Income Group Year 2000 (WB)

Although these coefficients are statistically significant, their size is small to support that institutional or macrolevel variables consistently affect the decision to adopt auctions. For instance, an increase of 1 point in FDI is associated with 0.104 extra years in the length of the treatment, and a 1-point increase in inflation explains a reduction in 0.070 years. For *rle*, a change of approximately 1 point explains a change of 0.093 years in the length of the treatment. These results have implications for the identification strategy because the small size of the coefficients indicates that the quality of the business environment has only a marginal influence on the choice for RE auctions. Thus, based on these observed variables, we cannot conclude that substantial and systematic differences between countries affect the decision to adopt auctions early on. Nonetheless, we still include the variables FDI, inflation, and the rule of law in our causal inference models. By adding these variables, we are controlling for covariates that could be correlated with the outcome and treatment adoption.

c. Subsampling according to the business environment

In this step, we classify countries according to the quality of their business environment, which is a necessary step to answer our research questions. We work with the four macroeconomic and six institutional variables related to business environment (see ***Table 3.1***) and combine two tools—PCA and cluster analysis—which are suitable for reducing the dimensionality of a dataset and finding subgroups within a particular sample. This is useful in our case for defining subgroups of countries according to the characteristics of the business environment. We conduct these analyses using the sum of currency and debt crises for the period and the country averages for the other variables.

First, we run a PCA analysis to reduce the dimension of the data using the R package *stats*. Then, we extract the scores of the first three dimensions that explain most of the variability and run a cluster analysis of those scores using the k-medoids approach (partitioning around medoids). This approach is more robust than the k-means, being less sensitive to outliers (Kaufman & Rousseeuw, 1990). Finally, we use the R packages *factoextra* (Kassambara & Mundt, 2020) and *cluster* (Maechler et al., 2022) for the estimation procedure. With this approach, we end up with the business environments of 40 countries classified as high quality and the remaining 58 classified as low quality. The methodological details are presented in **Appendix 3 *4***, and the countries classified in each group are shown in **Appendix 3 *5***.

d. Calculation of average treatment effect on the treated

To estimate the causal effects of auctions on the deployment of RE, we use a DiD estimator. The canonical form of DiD, which includes two groups (treated and untreated) and two periods (before and after treatment), recovers, under the parallel trend assumption, what is known as the *average treatment effect on the treated* (ATT). This is the difference between the treated potential outcome (y_t^1) and the untreated potential outcome (y_t^0) for all the units that have been treated and is expressed as follows:

$$ATT = E[y_t^1 - y_t^0 | treated = 1] \tag{3.3}$$

With multiple periods, not every unit might receive the treatment simultaneously (known as "differential timing"). The standard approach, in this case, is the TWFE model with the following model specification:

$$y_{it} = \theta_t + \vartheta_i + \gamma X_{it} + \beta treat_{it} + \varepsilon_{it} \tag{3.4}$$

where θ_t are period fixed effects, ϑ_i are individual fixed effects, X_{it} is a set of covariates, and $treat_{it}$ is a binary variable that reflects the treatment status (1 if individual i is treated in period t; 0 otherwise). In this case, β is the parameter of interest. This is the first type of model used in this chapter.

Previous studies that analyze the impacts of RE auctions have relied on TWFE for their empirical analyses (see **Appendix 3 *1***). However, estimating the parameter β may be biased when treatment effects are heterogeneous across units. For example, Goodman-Bacon (2021) shows that β is a weighted average of all the possible two-group-two-period combinations in the data. In this weighted average, the early (or past) treated units are used as controls for the later (or future) treated units (Goodman-Bacon, 2021). Because in this case the units used as controls are already treated, the parameter β in the TWFE may be biased.

Many of the recent developments in the DiD methods seek to account for heterogenous treatment effects in differential timing settings (Athey & Imbens, 2022; Borusyak et al., 2021; Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Gardner, 2021; Sun & Abraham, 2021). Based on this premise, we run two additional models.

The first DiD model we will use is the one developed by Callaway and Sant'Anna (2021) (hereafter CS). Their target parameter for identification is defined as the *group-time average treatment effect.* This is an extension of the ATT in the canonical 2x2 DiD but accounts for the fact that units adopt the treatment in cohorts (groups). It is specified as follows:

$$ATT\ (g,t) = E\left[y_t^g - y_t^0 \middle| G_g = 1\right] \tag{3.5}$$

This is the average treatment effect for treated units that belong to a particular cohort (g) at a specific time (t).

One of the most attractive features of CS compared with similar methodologies is aggregation. With many groups and periods, the large number of group-time average treatment effects may not be informative, so aggregated measures are preferable. The authors propose an aggregation procedure of the form:

$$\theta = \sum_{g\epsilon G} \sum_{t=2}^{\tau} w(g,t) * ATT(g,t) \tag{3.6}$$

In this case, $w(g,t)$ represents a weighting method, the choice of which depends on the type of information needed and the specific research questions[24]. At the same time, the methodology allows accounting for overall treatment effect parameters, i.e., summarizing everything into one parameter to show the overall effect of the treatment. According to the authors, the best way to obtain a general-purpose parameter is the following (Callaway & Sant'Anna, 2021, p. 12):

$$\theta_{sel}^{o} = \sum_{g\epsilon G} \theta_{sel}(g) * P(G = g | G \leq \tau) \tag{3.7}$$

This indicator is the sum of the average effect of participating in the treatment for each cohort $(\theta_{sel}(g))$ weighted by the probability of belonging to that specific group $(P(G = g|G \leq \tau))$, which in practical terms is the relative share of a group over the total number of treated units. This aggregated measure shows the average treatment effect for every unit treated during the period under analysis[25]. Given the small cohort size in our data, we will only focus on this type of aggregated measure.

For estimation purposes, we use the R package DiD developed by the authors (Callaway & Sant'Anna, 2022a). This package allows setting several estimation parameters: the estimation procedure (outcome regression[26], in our case), the aggregation procedure (group effects, in our case), and the comparison group ("not yet treated," in our case). In addition, to test for parallel trends before treatment, we use the event-study plots (Callaway & Sant'Anna, 2022a), presented later in the chapter (***Figure 3.6***).

The second DiD model we use follows a somewhat different estimation procedure. It is called two-stage DiD (hereafter 2SDID) and was developed by Gardner (2021). The intuition behind this method

[24] The authors propose three aggregation methods: dynamic (how the treatment effect varies with the length of exposure to the treatment), group (how the treatment effect varies according to cohort membership), and calendar (how the treatment effect varies according to calendar time).

[25] This concept is equivalent to the average treatment effect on the treated from the canonical 2x2 DiD.

[26] Given the nature of our research setting, we have multiple groups of small size, and the overlapping condition is weak (see **Appendix 3 *6***). For these cases, the authors suggest the outcome regression approach (Callaway & Sant'Anna, 2021, p. 13). This estimation procedure requires accurately modeling the expectation of the outcome evolution for the control group.

is that the untreated potential outcomes ($y_t^0|\ treated = 0$) decompose into group and time effects (Cunningham, 2021). Thus, the error term in the TWFE (ε_{it}) is "not mean zero conditional on group membership, period and treatment status" (Gardner, 2021, p. 6). Compared to CS, which works with group-time effects as building blocks for the analysis, this method follows an imputation approach, i.e., it imputes the value of the counterfactual $y_t^0|treated = 1$ using untreated units. It has the advantage of simplicity and shows efficiency gains compared with CS when the parallel trend assumption holds (Borusyak et al., 2021). However, when the parallel trend assumption holds conditionally, 2SDID is less stringent for dealing with covariates than CS.

The procedure proposed by the author takes two steps. The first requires removing those group and period fixed effects using untreated observations to predict the outcome. So, we run a TWFE regression of the type:

$$y_{it} = \theta_i + \vartheta_t + \varepsilon_{it} \tag{3.8}$$

where θ_p are period fixed effects, ϑ_g are group fixed effects. Then, we calculate the adjusted outcome as follows:

$$\hat{y}_{it} = y_{it} - \hat{\theta}_i - \hat{\vartheta}_t \tag{3.9}$$

The second step requires using this transformation as the outcome and regressing it on the treatment D_{gp} in the following way:

$$\hat{y}_{it} = \beta^{2s} D_{it} + u_{it} \tag{3.10}$$

In this case β^{2s} recovers the true ATT. We use the R package did2s developed by Butts and Gardner (2021) for the empirical estimation. Observations are weighted by the size of their group cohort to keep coherence with the CS group aggregation (see **Appendix 3 *6***).

Finally, we include covariates in our models to cover at least a conditional parallel trend assumption. The approach for dealing with covariates varies according to the model. Callaway and Sant'Anna (2021) suggest that covariates should be chosen to explain the evolution of the outcome in the absence of treatment (i.e., covariate-specific trends). Gardner (2021) does not include covariates in his model. However, he suggests that including time-varying covariates in the first- and second-stage regressions may be a simple way to deal with them (Gardner, 2021, p. 9)[27].

In our analysis, we propose three alternative specifications for each of our models:

(i) *No controls* (assuming the parallel trend assumption is fulfilled unconditionally);

(ii) *Controls (1)*: A set of control variables related to the country's energy profile usually used in the literature. We control for feed-in policies; GDP per capita (in 2015 USD); fossil dependency (oil rents, share of electricity produced through fossil sources, and CO_2 emissions); import dependency (net imports of electricity); and the natural endowment for solar, wind, and biomass.

(iii) *Controls (2)*: The set of variables in controls (1) plus specific variables related to macroeconomic stability and institutional quality.

We first run all three estimators (TWFE, CS, and 2SDID) and the three specifications for the full sample of countries, and then we run additional regressions including only those countries with high-quality business environments (*high_qual*) and only those countries with low-quality business environments

[27] However, as we mentioned above, the author recognizes that this approach is less stringent than CS.

(*low-qual*). This allows us to estimate the average impact of RE auctions and analyze whether these outcomes vary depending on countries' business environments. Finally, to analyze the effects of auctions on different RE technologies, we run our three estimators using the specification "Controls (2)" by the total capacity of solar, wind, and biomass separately. In every model, the standard errors are clustered at the country level.

As reflected in ***Table 3.1***, some variables are time-variant, whereas others are not. The TWFE and 2SDID models rule out time-invariant variables. In contrast, the CS package (2022a) explicitly requires pretrend time-invariant variables and automatically sets time-varying covariates to a base period[28]. Therefore, we include time-variant variables where possible and interact time-invariant variables with a trend variable. In the 2SDID model, we add the same set of covariates in both stages of the regression. As for the macrolevel and institutional variables in controls (2), we choose the ones that are significant in the Poisson models[29] (explained in subection 3.4.b), as they suggest that those variables influence the decision to adopt auctions.

3.5 Results

a. The effect of auctions over the share of RE in total system capacity.

This article examined the effectiveness of auctions for promoting RE investments under different business environments. In ***Figure 3.3***, we plot the coefficients of the effects of auctions for our three models and three specifications. The estimates for the entire sample and the subsamples of countries with high-quality and low-quality business environments are shown. All the coefficients are expressed as the increase in the share of RE over total system capacity (additional percentual points, p.p.) caused by adopting auctions.

The first group of estimations is calculated over the whole sample, with 98 countries. Overall, we find that the adoption of auctions has a positive effect on the share of RE capacity in the energy matrix. For the full sample, the results range from 1 to 2.90 p.p., all significant at least at the 10% level. Previous papers have found even smaller effect sizes; for instance, Kilinc-Ata (2016)[30] found an effect of approximately 0.7% for tendering mechanisms.

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[28] The base period is "the period immediately before observations in a particular group become treated" (Callaway & Sant'Anna, 2022b)

[29] In the TWFE and the 2SDID, we will interact the 2000 level of those variables with a time trend variable, which is the approach used by Hoynes and Schanzenbach (2009). For the CS model, the variables are included at their baseline level.

[30] The rest of the papers that assess the effectiveness of auctions from a quantitative perspective use different dependent variables, hindering results comparisons.

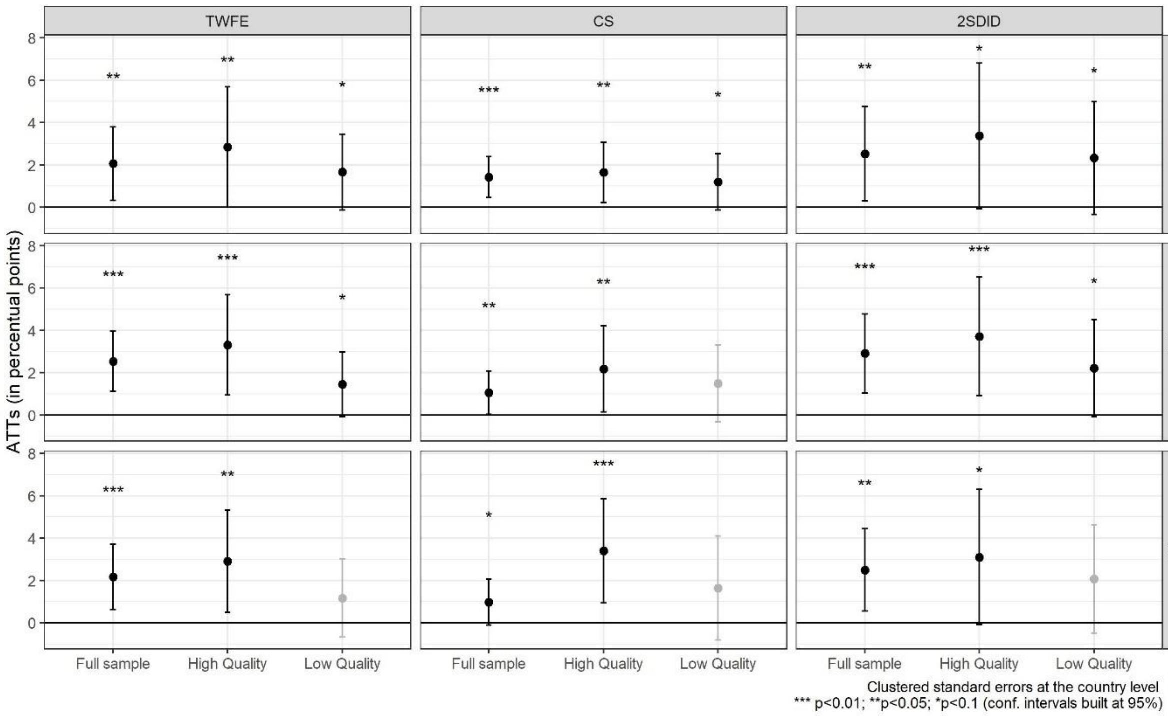

Figure 3.3. Average treatment effects (ATT) of auctions on RE as share of total installed capacity. Point estimates from all three models (TWFE, CS, and 2SDID) are shown with 95% confidence intervals. Grayed-out point estimates indicate that the coefficient is not statistically significant ($p > 0.10$). Rows indicate different model specifications: *"no controls"* assumes that the parallel-trends assumption is fulfilled unconditionally*; "controls (1)"* include as covariates feed-in policies, GDP per capita (in 2015 USD), oil rents, the share of electricity produced through fossil sources, CO_2 emissions, net imports of electricity and the natural endowment for solar, wind and biomass; and *"controls (2)"* additionally controls for inflation, FDI, and the rule of law.

We then conduct the subsample analysis, dividing countries according to the quality of their business environment. Countries that are stable from a macroeconomic perspective and have high-quality institutions are considered high-quality. In contrast, countries with some degree of macrolevel instability and less stable institutions belong to the low-quality group. **Appendix 3 *5*** presents the complete list of countries and their classifications.

There are two main aspects to highlight from the subsample analysis. The first is that, in every model specification, the results are significant at least at the 10% level for countries in the high-quality group. The same is not true for countries in the low-quality group, however, for which we find significant results only for some model specifications. The second aspect relates to the size of the coefficients: the effects are always more significant for countries in the high-quality group. In specifications that include all the control variables, the estimations range from 2.90 to 3.40 percentual points for countries in the high-quality group, whereas estimations for the low-quality countries range from 1.17 to 2. Auctions have consistently been more effective for the period under analysis in countries with a more stable business environment. The reasons behind these results will be discussed in the next section.

Given that the results may be affected by how countries were classified into the two groups, we use an alternative approach to categorize the quality of countries´ business environments as a robustness check. This is explained in **Appendix 3 *4***. The results of this alternative procedure are presented in **Appendix 3 *7*** and do not differ substantially from the main analysis.

b. The effect of auctions for each RE technology

Our second research question asks whether the results differ substantially according to the type of renewable technology. In ***Figure 3.4***, we present the results disaggregated by RE technology. Our models do not have an indicator to account for technology neutrality or specificity of auctions. Therefore, the results are primarily exploratory and should be treated with caution. We change the outcome variable in each case to study the share of each specific technology over total system capacity (reasonably, we expect lower results in absolute terms).

Here, the results are less conclusive; nevertheless, we can identify some general trends. We find significant results in some models for wind technologies in the high-quality group. Wind power has had a considerable uptake in Europe, both onshore and offshore (IRENA, 2019, p. 10). In contrast, we find significant results for solar and biomass in the low-quality group. Countries in Africa and Southeast Asia have prioritized solar projects (del Río & Kiefer, 2021; IRENA, 2019, pp. 11–12). Biomass is behind wind and solar technologies in terms of the volumes auctioned. Still, countries in South and Central America and Southeast Asia are seeking to exploit their biomass potential. In contrast, European countries have disincentivized crop biomass due to potential land-use changes and food-energy competition (Scarlat et al., 2018).

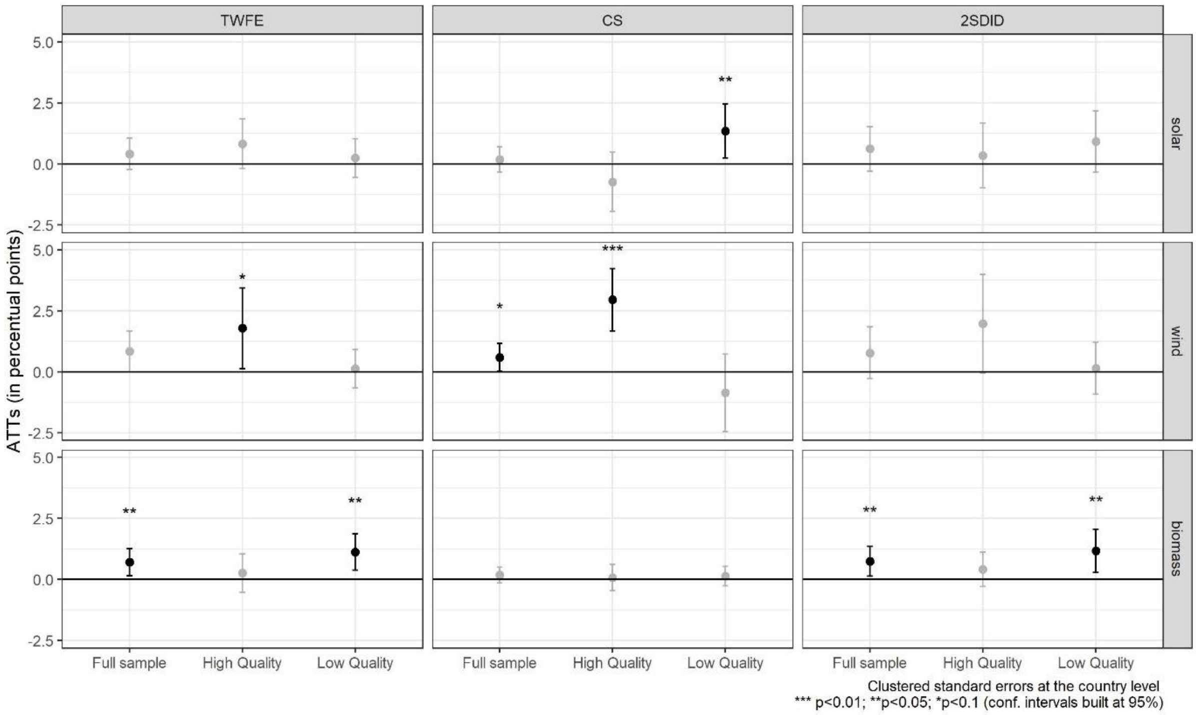

Figure 3.4. Average treatment effects (ATT) of auctions by RE technology.

Point estimates from all three models are shown with 95% confidence intervals. Grayed-out point estimates indicate that the coefficient is not statistically significant (p > 0.10). Rows indicate the effects disaggregated by RE technology. In all models, we use the covariates from "controls (2)."

3.6 Discussion

In terms of the aggregated effects, we observe an increase in the share of RE capacity due to auctions. The effect size for the whole sample ranges from 1 to 2.9 p.p. and is higher for countries with stable business environments. Despite its small size in absolute terms, this is still promising compared with the evidence for other policy instruments from the literature. For feed-in tariffs, the evidence is mixed: Kilinc-Ata (2016) found a positive effect of approximately 2.8 p.p. over the ratio of RE capacity, whereas Aguirre and Ibikunle (2014), Bento (2020), and Popp et al. (2011) found no significant effects. Romano et al. (2017) even found a negative impact of feed-in tariffs. While these traditional policies have been drivers of RE, they have reached a saturation point; countries are now exploring new instruments, especially considering that policy accumulation does not necessarily lead to better outcomes (Zhao et al., 2013).

Despite the fast adoption rate of RE auctions in low and middle-income countries and some potential advantages in contexts with macroeconomic and institutional instability, our results show better outcomes in countries with stable business environments. What are the reasons for these results? We present four different lines of explanation.

The quality of infrastructure is the first factor that could undermine the effectiveness of auctions. As we see in ***Figure 3.5*** panel (b), the perception of infrastructure quality is more favorable in countries in the high-quality group. Private investors may be discouraged from participating in auctions if they anticipate difficulty accessing energy grids (del Río & Linares, 2014; Gephart et al., 2017). Even when they do participate in auctions, the administrative failure to provide expeditious access to the networks results in construction delays and higher implementation costs (del Río, 2017; del Río & Kiefer, 2021).

The second reason for the variable effect of RE auctions is the absence of an auction schedule in some countries, which might lead to auctions taking place sporadically. According to del Río and Kiefer (2021), European countries have tended to schedule their auctions, which is not the case for other regions. As a result, private actors might be reluctant to invest if they do not foresee consistent auction planning (Hochberg & Poudineh, 2018; IRENA, 2019). ***Figure 3.5*** panel (a) shows the proportion of years in which countries effectively performed subsequent auctions after implementing the first one[31]. While the median for countries in the high-quality group is above 0.5, it is lower in the case of the low-quality group.

Running auctions regularly is relevant because of dynamic effects. In ***Figure 3.6***, we present event-study plots. These plots show the effect size (y-axis) according to the length of the treatment (in the x-axis). Negative values represent the periods before the units adopted the treatment (lags). The fact that these coefficients are close to zero and nonsignificant indicates that the pretesting of the parallel-trends assumption is fulfilled. Positive values represent the variable's leads, showing the policy's effects according to the length of exposure to the treatment. It is evident that the average treatment effects grow over time. This implies that countries must capitalize on lessons from the initial rounds and stick with the instrument to see consistent results (IRENA & CEM, 2015).

[31] Countries with <2 years into the treatment were excluded.

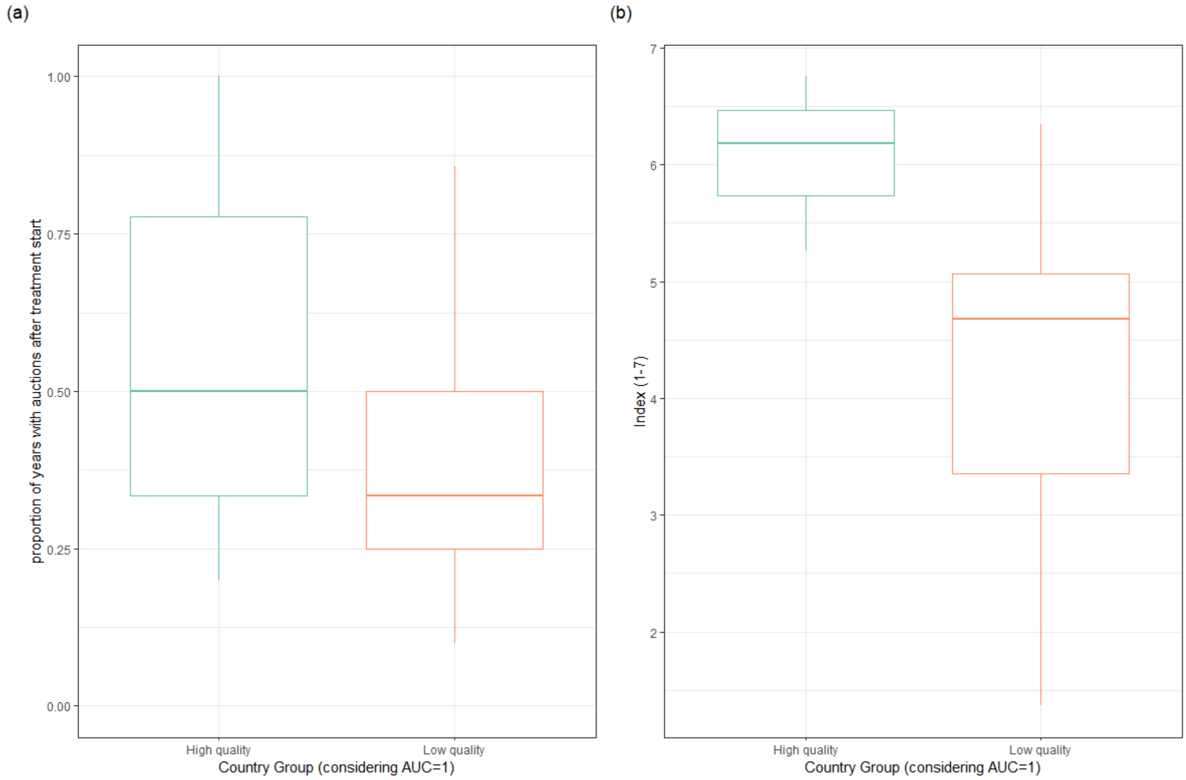

Figure 3.5. Panel (a). Frequency of auctions. Panel (b). Perceived quality of infrastructure.
Panel (a). The proportion of years in which countries have effectively launched auctions after implementing the first one (for countries that have adopted auctions before 2019). *Panel (b).* In your country, how reliable is the electricity supply (lack of interruptions and lack of voltage fluctuations)? [1 = extremely unreliable; 7 = extremely reliable] (World Economic Forum Global Competitiveness Index).

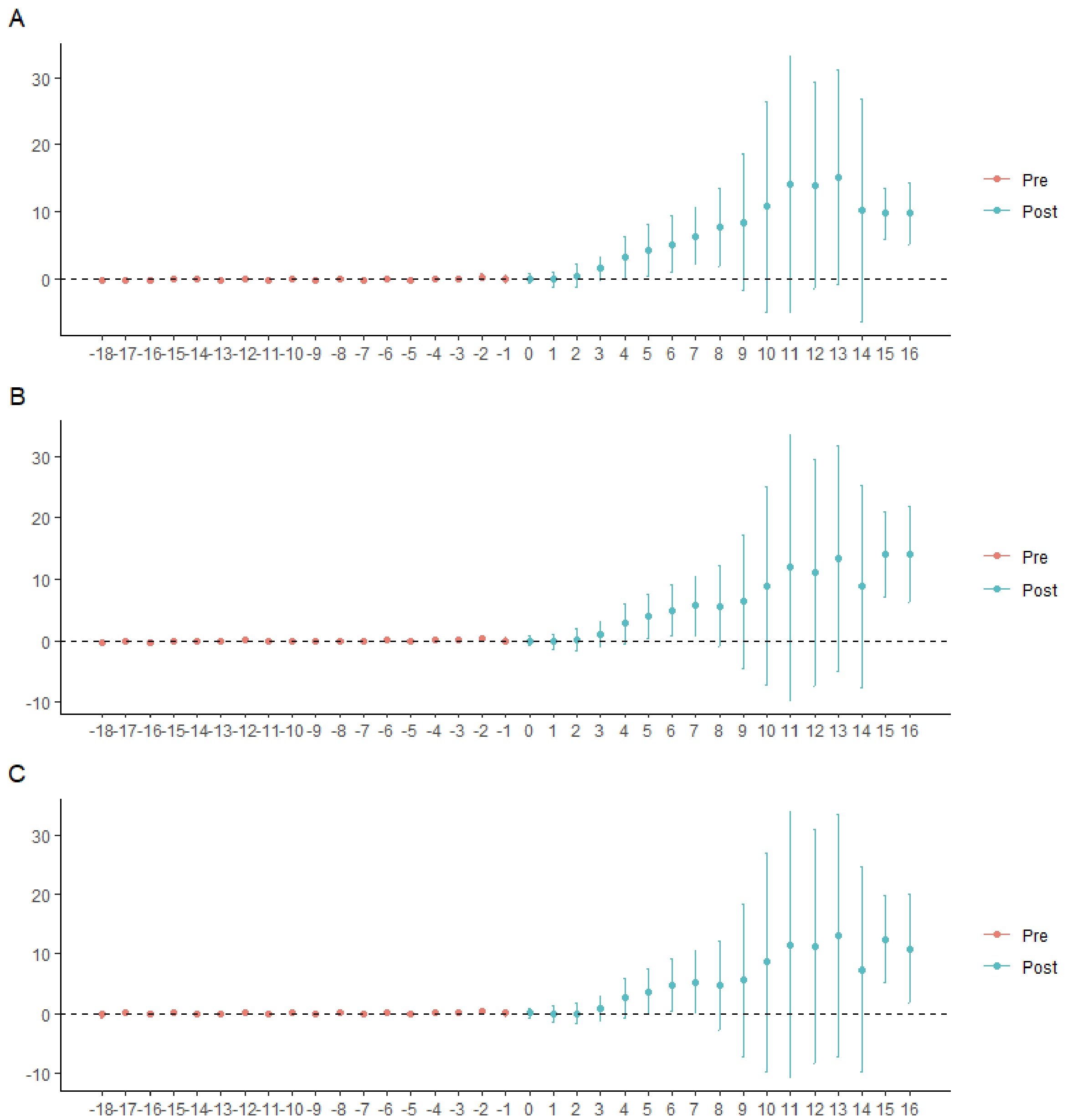

Figure 3.6. Event-study plot to test for parallel pretreatment trends.
This figure presents event-study plots for three scenarios of control variables as explained in subection 3.4.d: no controls in panel A, controls (1) in panel B, and controls (2) in panel C. In each case, the parallel trend condition is fulfilled before treatment (period 0) because we do not see any significant coefficients.

The third factor is that auction programs can still fail in construction despite high realization rates. For auction winners, setting up the physical and administrative infrastructure requires time and money. If financial or macroeconomic conditions change in the middle of the construction process, this could result in unexpected delays or early project termination (Gephart et al., 2017). Inefficiencies and delays have been frequently reported in countries such as Peru, Brazil, China, and India (del Río & Kiefer, 2022; del Río & Linares, 2014; Kreiss et al., 2017).

A fourth reason auctions perform worse in countries with unstable business environments relates to design flaws. Many countries include additional features that do not always contribute to the success of tendering schemes. For instance, there has been a trend toward including Local Content

Requirements (LCR) in developing countries. In such cases, auctions are considered both an RE policy and a means to promote local development (del Río & Kiefer, 2021). However, excessively stringent requirements or a lack of complementary measures to build local value chains could severely undermine the effectiveness of the auction program. Such delays due to mismatches between LCR schemes and local capacities have been reported in Brazil, South Africa, and Indonesia (del Río, 2017; Dobrotkova et al., 2018; IRENA, 2013).

3.7 Conclusions and policy implications

Auction mechanisms promise to promote investments in RE at lower costs than conventional support mechanisms. Accordingly, many low and middle-income countries rapidly adopted this policy instrument in the last decade. Nevertheless, the effectiveness of tendering schemes has been mainly assessed in OECD or European countries, where the business environment is generally stable. This chapter presented a quantitative evaluation of RE auctions, exploring whether the effectiveness of this policy in fostering RE capacity varies according to the quality of the business environment (defined as a combination of macrolevel stability and institutional quality).

We make an important empirical contribution by considering heterogeneous treatment effects and staggered policy adoption. TWFE models, widely used in the literature, may recover a biased ATT in the presence of heterogeneous treatment effects. To address this shortcoming, we use novel DiD methodologies to provide more robust results, which are then compared with the more standard TWFE approach.

Overall, our analysis finds that auctions contribute to increasing the share of RE over total system capacity. However, the adoption of this policy should be undertaken with caution. Despite the prevailing optimism, the results still appear to be modest for countries whose business environment is not optimal. Moreover, previous qualitative case studies have already suggested the need for caution in the case of RE auctions (Cassetta et al., 2017; Grashof et al., 2020; Winkler et al., 2018).

The findings in this chapter have three main policy implications. The first relates to how governments in countries with unstable business environments manage uncertainty. Auction mechanisms can be designed to provide long-term contracts with safeguards against inflation or devaluation but cannot rule out every single source of risk. Additional measures to complement auction programs may help mitigate risks and instill confidence in investors. One possible way to achieve this is by engaging multilateral institutions. For example, the involvement of the World Bank in providing additional warranties in the Scaling Solar project in Africa or the RenovAR program in Argentina has shown promising results (The World Bank, 2018, 2019). Another option is to include decontracting auctions in which companies are permitted to bid for a fine and cancel the project (IRENA, 2017). This could provide additional safeguards against unexpected changes in the business environment.

A second policy implication involves the frequency with which countries launch RE auctions. In countries with weak business environments, significant RE capacity increases will only occur if investors anticipate the government's intention to maintain the policy in the long run. Moreover, our analysis showed dynamic treatment effects, implying that the impact of implementing auction programs increases gradually. Thus, there is a learning curve in which countries must learn from past mistakes and continually fine tune the design features. Various studies have shown that accuracy in design is critical for the success of tendering mechanisms (del Río, 2017; Matthäus, 2020; Winkler et al., 2018).

The third policy implication is that auction programs should consider countries' technological capabilities and natural resource endowment. This is key for developing countries where public budgets are typically limited. For instance, we saw that auctions contribute to increasing the share of biomass energy in countries with low-quality business environments (***Figure 3.4***). Although biopower projects have higher initial investments and operational costs (FAO, 2020b), auctions could be suitable for fostering this technology in countries with a biomass surplus. Investments in biomass-based electricity foster the cascading use of waste from agricultural and agroindustrial production and provide a low-carbon reserve capacity for the system (Johansson et al., 2019).

Because auctions are gradually becoming the dominant RE policy choice worldwide, a critical assessment of the effectiveness of RE auction mechanisms is needed. Nevertheless, our study has certain limitations. The first is the size of the cohorts of adoption. Even when we focus on aggregate measures, such small groups widen the confidence intervals and reduce estimation quality (especially in the CS methodology). The second limitation involves treatment irreversibility. The DiD approaches we applied in this study are designed for staggered adoption and do not consider treatments that switch on and off. Future models should consider the frequency of use and the learning effects implicit in auction mechanisms. A third point relates to policy stringency: pricing mechanisms, penalties, and physical or financial requirements are critical features for safeguarding the instrument's effectiveness; however, the definition of the treatment in this study does not include these features. Further research should consider them to account for the fact that some countries might be more rigorous in their policy design. Finally, differentiating the auctions by technology could help discover nuances or specificities for each RE source that could improve the design of auctions.

General conclusions and discussion

Unlike any other period in human history, technical change is now driven by the need to steer the economic production system in a trajectory that ensures economic growth without compromising the natural capital for future generations. However, changes in the technological dimension are not isolated from the surrounding institutional environment. Institutions, a set of human-designed rules that facilitate economic and social interactions in a society, mediate the technological change process by creating a governance setting for innovation decisions (such as in which technologies to invest or whether it is worth adopting a new solution), but also how the benefits of those new technologies are distributed among actors in the society.

This doctoral dissertation addresses the nexus between technological change, policies, and value chain governance for a transition towards a low-carbon economy. Sustainability-driven technical change can be rooted in value chain organization and governance (as discussed in Chapters 1 and 2), in specific public policies (chapter 3), and in corporate interests and investments (chapter 2). Each of these governance drivers has different implications and challenges, and this is explored in this dissertation in three separate chapters with specific research goals: (1) understand the role of value chains in fostering bioeconomy innovation, (2) analyze the links between technological innovations and the industry structure in agri-food GVCs and (3) understand the role of policy design in reaching low-carbon energy systems, focusing on renewable energy auctions.

Summary of findings

Each chapter in this dissertation was presented as a conceptually individual unit, but three core ideas structure the discussion and intersect the three chapters simultaneously. This is summarized in **Figure C *1***. The first point in common is that changing the technological foundations of the current economic system toward environmentally cleaner technology is inexorable in front of the climatic crisis. Chapter 1 (Ch.1) focuses on bio-based technologies. The bioeconomy is one of the potential pathways to mitigate GHG emissions and create new economic opportunities, but simply replacing fossil raw materials with biomass feedstocks entails possible environmental side effects that could offset potential gains. Ensuring a sustainable transition requires a shift from biomass-intensive technologies toward advanced stages involving higher-generation feedstocks, the adoption of circularity principles, and the design of new biosynthetic compounds. Chapter 2 (Ch.2) delves into innovations to improve global agri-food value chains. Different estimations show that agri-food systems are responsible for between one-quarter and one-third of global anthropogenic emissions (Crippa et al., 2021; Poore & Nemecek, 2018), while substantial investments are still needed to end hunger. However, in the last fifteen years, most venture funds have been oriented toward downstream technologies (e.g., food service or delivery solutions) based on digital solutions. Upstream technologies that promise a more sustainable biomass production have been less attractive to funds, so there is space to improve funding opportunities around farming technologies. In Chapter 3 (Ch.3), attention is placed on renewable energy. Energy systems account for around 34% of total GHG emissions (Lamb et al., 2021), so investments in solar, wind, and biomass energy sources will contribute toward reaching low-carbon energy systems. The cost of renewable energy has fallen in the last decade (especially photovoltaic technologies), but countries need to consider their technological capabilities and natural resource endowment to define the best renewable mix (especially in developing countries where public budgets are typically limited).

A second central idea that crosses the three chapters is the nexus between a specific governance dimension and technical change. The first two chapters explore value chains as vehicles for technical change, delving into the interaction of organizational features of value chains and innovation. The third chapter studies policy innovation and institutional infrastructure to promote investments in renewables. Some institutional contexts may be more conducive to accelerated technical change, while others may hinder it. Business environments with lower conflict rates or more willingness to collaborate and share knowledge (Ch.1), industrial leaderships that align incentives in the value chain (Ch.1 and 2), and stable policy and macroeconomic environments (Ch.3) are among the factors discussed along this dissertation that help to promote sustainability-driven technical change and innovation. Simultaneously, as technological change modifies the economic production function, it also shapes the institutional setting in society and creates new governance rules. Many of the recent accelerated changes in technologies oriented to sustainability, such as advances in biotechnology, renewable energy sources, massive digitalization, and artificial intelligence, require new institutions: regulation schemes that favor clean technologies against fossil-based sources (Ch.3), research systems that foster knowledge sharing and research interaction between government, universities and private sector (Ch.1), supply chain coordination mechanisms that transmit new consumer demands and align actors toward more sustainable production canons (Ch.1), new financial sources that understand the complexity of innovation (Ch.2).

A final idea underlying the three chapters is that, without the right institutional design, technical change is neither a sufficient condition for the conservation of the environment nor for the inclusion of the weakest economic agents. As value chains become more technology-intensive, this affects the welfare of different actors and may create a redistribution of benefits among them (Ch.1). Potential challenges from a social sustainability perspective are related to uneven access to technology (e.g., farmers that cannot access new seed traits or agricultural inputs, or patients that cannot afford new biotechnology-based therapies), the exclusion of smallholders or SMEs by dominant value chain firms (e.g. due to closed cross-licensing schemes) or the failure to transfer technology toward developing economies. Moreover, even when many science- and tech-based start-up companies are driving accelerated innovation at a niche level, whether these ventures will materialize in actual benefits for the environment and society depends critically on the behavior of large incumbent firms (Ch.2). The industrial dynamics in which these companies can prioritize technology canons, control global distribution networks, or establish production standards will determine whether many clean technologies will succeed in going from the development to the commercialization and diffusion stages and fulfill their promises. Even when specifically targeted policies may foster investments in clean technologies, this may not be sufficient for decarbonization (Ch.3). Policymakers´ determination is necessary, but the characteristics of the institutional and macro-level environment and hard-wired technological lock-ins may create resistance and reduce the efficiency of public policies.

Core guidelines / Chapter	Chapter 1	Chapter 2	Chapter 3
Technological innovation is required to promote environmental sustainability.	Bio-based innovation implies moving from traditional high-volume and low-value applications toward technologies that create economic value while reducing biomass requirements.	Technological innovations in global agri-food value chains are necessary to secure healthy and affordable diets within planetary boundaries.	Low-carbon electricity systems based on renewables contribute 1.5-2 temperature limits, considering energy systems explain the largest share of global anthropogenic emissions.
Several governance challenges come along with technical change.	Some organizational structures in value chains may be more conducive to fostering bio-based innovation.	The success of many cutting-edge technologies in improving food systems is conditioned by industrial dynamics, given the high levels of market concentration in global agri-food value chains.	Policy innovation and institutional infrastructure are required to design adequate remuneration schemes in renewables.
Technical change is not a sufficient condition for a sustainable transition.	Innovation-intensive bio-based value chains create trade-offs between GHG emissions mitigation and social inclusion.	The new socio-technical regime in which innovation is revolutionizing food systems holds the risk of being held up by lock-ins from the current system.	Public policies are needed to create incentives in favor of clean technologies, but the institutional environment can undermine their effectiveness.

Figure C 1. Summary of the main approach and findings in each chapter.

Policy implications

This dissertation holds several contributions from a policy perspective. Policymakers are expected to manage trade-offs between potentially conflicting goals to ensure that an environmentally sustainable transition is also socially inclusive. While synergies between economic and social dimensions may emerge more clearly, balancing these two dimensions and environmental goals is not always straightforward and requires fine-tuning in policy design and negotiation with stakeholders. In this line, three main policy implications can be drawn from this dissertation. The first point is that as technology becomes more complex and environmental requirements become more stringent, some actors may become entirely displaced from the value chain. Without necessarily changing the natural course of a technological transition, policymakers should still be able to mitigate potential harmful effects to safeguard the interests of the weakest value chain actors. Policies should explore the potential of low-scale technologies with fewer capital requirements that fit smaller value chain actors (Kaplinsky, 2011), such as biomass processing equipment at the farm level, or even favor new developments built upon old technologies with expired patents (Yun et al., 2021), like new seed traits that work with old-fashioned herbicides or insecticides. This way, small farmers in the upstream segment could still be part of more technology-intensive value chains. Moreover, it is necessary to foster incremental innovations that follow disruptive developments, which could create benefit spillovers toward small and medium enterprises (Perez, 2010).

A second relevant aspect from a policy perspective is the correction of failures in the private venture capital markets. Venture capital is a critical tool for start-ups but is not exempt from failures: investors normally chase immediate profit promises, which technologies with high decarbonization potential cannot offer in most cases. Innovation in life sciences and agriculture is risky because it has long payback periods, requires considerable capital investments, and depends on living organisms that are not always controllable. On the contrary, building blocks for the downstream segments (such as e-commerce or digital food service) are much more mature and appear as the low-hanging fruit for investment funds, with faster investment returns and higher adoption potential. However, upstream activities related to the farming stage explain the largest share of the anthropogenic emissions, so policy action is needed to correct biases in the venture capital systems and support technologies that promote sustainable food and biomass production while reducing pressure on land requirements (i.e., biological inputs, new biotechnology traits, farming robotics or animal proteins substitutes). The type of private investments these technologies need is not the same that worked for the computer or digital technologies industries in the past. A more active role of the government as an investor, in partnership with private actors, is a possible way of correcting these biases (Mazzucato, 2015). Moreover, discussing alternative financial schemes that do not (exclusively) rely on venture capital, but that account for more long-term and organic growth of the companies would imply lower requirements for minimal returns compared to venture funds. Another way is the development of geographically focused agricultural technology ecosystems, in which Universities, start-ups, research institutes, and the government collaborate actively with a long-term view to support companies in their nascent stages, which are not the focus of large private equity or investment management funds. Several efforts are taking place to foster start-up communities in South America and Africa (Berkland et al., 2018; Paquette et al., 2023).

A third aspect to consider is that policy design should necessarily account for the characteristics of the socio-political context. This is especially true for developing countries facing instability or having a lower quality of their rule of law. Innovative policies that proved successful in one country or region may not work in economies more exposed to currency crises, fluctuating interest rates, or weaker contract enforcement. Developing nations should not simply copy recipes that have worked in developed countries but emphasize accurate design to ensure the consistency between policy instruments and goals. For example, in the case of the Renovar program in Argentina, the government introduced a triple-level guarantee (including the involvement of the World Bank) to send a strong signal to investors in a volatile macroeconomic context, which ultimately reduced the uncertainty for private capital and made the auction program successful. Moreover, policymakers in developing economies should also adapt their policy design to consider a situation in which IP rights are weak. Strengthening IP regulation is not among the main worries in developed nations, but in a context where economic growth is increasingly built upon knowledge and skills, many developing countries are experiencing the flourishment of new young companies doing research and promoting innovations, and consequently need to work on the proper institutional design for them (Arndt et al., 2019; Jack et al., 2021; Pulido, 2023). Improving IP regulatory aspects could contribute to correcting historical asymmetries in which developing economies are limited to biomass production while developed nations profit from innovation royalties (Ezell & Cory, 2019).

Business implications

The findings in this dissertation also have implications for business managers and entrepreneurs. While accurate and well-targeted public policies are essential, many of the changes needed to steer the economic system into more sustainable trajectories come from private initiatives. New strategic perspectives and business practices are required in front of sustainability-driven technical change. There are two main business implications from this work.

The first point is that the changing narrative around the role of businesses as agents of societal change is becoming a source of new entrepreneurship opportunities. The sustainability dimension, generally considered outside of the company's main business, has now turned out to be at the core of the strategy (Bonini & Swartz, 2014). As a part of this process, traditional business models are being redesigned to embrace these new strategies (Carraresi & Bröring, 2021). The concept of sustainability is now a source of value creation, creating many opportunities for small and medium companies in the innovation supply chain. Nevertheless, there are also new governance challenges for this type of business. Sustainability-driven innovation changes part of the organizational features and governance schemes in value chains, so new institutional mechanisms to organize transactions are needed. For example, putting a price on waste biomass, valuing ecosystem services, or pricing carbon to be commercialized is not always straightforward and requires discussions and agreements on the transparency of these practices (Popkin, 2023). Moreover, it is arguable whether biological resources can be directly turned into purely market assets (Pascual et al., 2023). Industrial concentration is also a challenge, considering that GVCs will continue to be ruled by a few large multinational companies that can steer technological change.

The second point related to business implications concerns dealing with risks and payback periods of innovation. Compared to the fossil-based dominant paradigm, built upon both mature technologies and developed markets, ventures focused on decarbonization depend on R&D activities whose success is not guaranteed and might face higher capital and operational costs. This can be even worse in the case of developing economies, where institutional and macroeconomic environments are less stable. A single company cannot have the complete set of capacities and financial resources required to deal with all these risks. Thus, open innovation practices such as company acceleration, business ecosystems, or strategic alliances are reasonable paths toward helping small companies and entrepreneurs mitigate innovation risks (Baum et al., 2000; Bogers et al., 2018). Moreover, in the long run, new accounting rules have to be promoted to recognize triple-bottom-line impact measures, considering environmental and social aspects in addition to standard economic metrics (Antonini & Larrinaga, 2017; Svensson et al., 2018). This way, companies that work with clean technologies may overcome the financial implications of the technological lock-ins of the current fossil-based paradigm.

Limitations and further research needs

Studying processes of technological change that are still at an emerging stage poses several methodological challenges. Many aspects linked to innovation require necessarily adopting a prospective vision, for which using (exclusively) historical data is insufficient. Thus, traditional quantitative methods used by agricultural economists need to be complemented by other qualitative, descriptive approaches. Moreover, publicly available data sources to study start-ups are limited, and many private actors are reluctant to provide details or specific quantitative information during interviews or data collection surveys due to confidentiality issues. This leads to two main points regarding future research.

The first point is that understanding the relationships between innovation and the surrounding institutional environment will become increasingly necessary in a world of exponential technological change. Research efforts should strengthen the interaction between development economics, value chain analysis, and industrial organization. These disciplines, which have historically developed independently, should foster communicating vessels and cross-pollination in theory and methods. Each of them has tackled from different perspectives the issues of how technological change emerges and the type of impact it creates in society. Still, the commonalities among the three of them have not been highlighted enough in scientific research.

A second point concerns data availability and database building to study innovation. Strengthening databases on entrepreneurship, venture capital, patents, and other aspects of developing new sustainability-driven businesses is necessary. Making this data publicly available to researchers interested in how innovation processes occur and the potential impacts of new technologies is critical in constructing innovation ecosystems. This is especially true for developing economies, where quantitative information is usually more limited. Further research should be oriented to develop new databases that help to study innovation more thoroughly, complementing case-study analyses with quantitative studies and other mixed methods.

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Appendices

Appendix Chapter 1

Appendix 1 1. Value chains in a bioeconomy upgrading.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Environmental impacts (ENV)	Mainstream use of first-generation technologies. Risks of environmental impacts in the long run due to land-use change.	Risks come from the use of first-generation technologies. However, there is a higher GHG mitigation potential in the case of waste and circular economy practices.	Risks come from the use of first-generation technologies. However, there is a higher GHG mitigation potential in the case of waste and circular economy practices.	The palette of feedstocks used is broad. The risk of externalities is mitigated when more efficient feedstocks are used (2nd, 3rd, and 4th gen).	The intensity of biomass processing is lower. This reduces GHG emissions and risks of land-use change.	The technological processes are not strictly based on biomass processing. Low risk of environmental impacts.
Economic Value Added (ECON)	Substitution of fossil-based products. High volume-low value.	Substitution of fossil-based products. High volume-low value. Local biorefineries can create new employment opportunities in rural areas.	Substitution of fossil-based products. High volume-low value. Local biorefineries can create new employment opportunities in rural areas.	Substitution of fossil-based products. The use of biomass is still intensive, but value-added is higher compared to models 1-3.	Low volume-High value. New products and processes.	Low volume-High value. New products and processes.

Appendix 1 2. Characteristics of the innovation process and the technologies involved.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
A.1 Technological risks	Mature, turnkey technologies. Biomass intensive. Efficiency and logistics are key to success.	Mature, turnkey technologies. Biomass intensive. In-place processing.	Mature, turnkey technologies. Biomass intensive. In-place processing.	Application of known technologies to new processes. Technologies are not fully mature (still expensive)—steep learning curve.	New conversion pathways with high risks of failure. Tailor-made technologies.	New conversion pathways with high risks of failure. Tailor-made technologies.
A.2 Level of investments required	Investment in fixed assets. Decreasing returns to scale.	Investment in fixed assets. Decreasing returns to scale.	Investment in fixed assets. Decreasing returns to scale.	Investment in fixed assets but also in R&D. Need to develop and protect IP.	High R&D Costs. Increasing return of scale. Regulation is an issue. Need to develop and protect IP.	High R&D Costs. Increasing return of scale. Regulation is an issue. Need to develop and protect IP.
A.3 Systemic characteristics	Diffusion of known technologies. Few systemic adaptations are required.	Diffusion of known technologies. Few systemic adaptations are required. The main changes are related to behavior and the adoption of circular practices.	Diffusion of known technologies. Few systemic adaptations are required. The main changes are related to behavior and the adoption of circular practices.	Invention-innovation phase. Increasing coordination is required. Production processes need to be adapted to incorporate new bio-products.	Highly systemic. New ways of production. New markets need to be created.	Highly systemic. New ways of production. New markets need to be created.

Appendix 1 3. Value chain features.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
B.1 Value chain governance	The procurement of biomass is mainly based on market mechanisms. Supply contracts can exist (but not necessarily).	Horizontal and vertical (forward) integration. Need for contracting schemes. Collection agreements may be necessary for waste.	Vertical integration. Collection agreements may be necessary for waste.	Biomass supply contracts are necessary, especially for higher-generation feedstocks.	Lead firms need to control the value chain. As a result, supply contracts and vertical integration are prioritized over pure market mechanisms.	Lead firms need to control the value chain, especially downstream.
B.2 Predominant industry structure	Many firms. Geographical concentration around biomass sources. Low leadership requirements.	Many firms. Geographical concentration around biomass sources. Some actors become local promoters of these initiatives.	Many firms. Geographical concentration around biomass sources. Some actors become local promoters of these initiatives.	Leader firms that foster the adoption of new bio-based products and services. Some degree of monopsony power may be created in the case of the 2nd, 3rd, and 4th gen of feedstocks.	Big industry players lead in bringing new technologies to market—shorter and tighter value chains. There is space for startups to explore new developments that call the attention of established firms.	Big industry players lead in bringing new technologies to market—shorter and tighter value chains. There is space for startups to explore new developments that call the attention of established firms.
B.3 Collaboration and open innovation	Low. Collaboration is not needed since technologies are already proven.	Some degree of horizontal cooperation among biomass producers is needed to gain scale in feedstock supply.	Collaboration for research is not needed since technologies are already proven.	Partnerships between technology developers and industrial clients. Research capabilities are needed.	Partnerships between technology developers and industrial clients. Research capabilities are needed.	Inter-industry collaboration. Space for industrial convergence.

Appendix Chapter 2

Appendix 2 1. Typology of Solutions. Details.

Solution	Details
Precision agriculture, smart farming, and farm robotics	Data collection, imagery, and information at the farm level: Crop sensors integrating IoT, satellite and drone imagery, yield monitors, telemetry systems, soil maps, and yield maps. Precision Agriculture: Automated Guidance, GPS/GNSS, variable rate technologies, smart irrigation systems, smart water management. Farm Robotics: Robots for weed control, harvesting, and disease detection; drones for fertilizer or pesticide spraying; autonomous farm technologies. Digital Advisory: Digital advisory and extension services (via smartphones, SMS) based on farm data analysis and processing. Farm Management Software: Software solutions to improve management at the farm level. Cloud-based solutions and information systems oriented to farm management. Precision Technologies for Cattle Raising: Accelerometers, automated heat detection, geofencing and virtual fencing, digital pasture management. Automated milking robots.
Biological inputs and solutions	Biological inputs: biocontrollers, biostimulants, biofertilizers, effective microorganisms, microbiome-based solutions Agri-nanotechnology: nano fertilizers, nano pesticides. Other solutions: natural pollination services.
Plant, Animal and food Biotechnology solutions	Gene Editing: Seed traits based on genome editing technologies (CRISPR-cas and similars) New Genetically Modified (GM) Traits: crop protection, abiotic stress, nitrogen fixation based on genetic engineering. Other crop varieties which are expressing enhanced product features (e.g., improved oil content). General Biotech Services: Companies providing biotechnology services in several verticals without a specific field, such as genomic services, bioinformatics, or genetic testing services (Probably part of these companies are producing improved crop varieties, but if this is not the main focus of their company description they are included in this category). We also include general bio-based raw materials, analytical services for manufacturing companies, biotechnology support services for food industries, and the development of nanomaterials and nano ingredients for the food industry. Animal Genetics: Animal breeding and genetic improvement in livestock; seafood genetics. Pharmaceutical Products: pharma and veterinary products for animal production; vaccines
Alternative ways of farming	Controlled-environment solutions: Indoor farming, vertical farming, urban farming, modular farming, aquaponics, hydroponics, and aquaculture. In general, production methods reducing the reliance on specific soil or weather conditions. Includes the production of equipment for hydroponics, aquaponics, and indoor farming (e.g., modular systems, greenhouse building, led lights for indoor farming). It also includes companies selling inputs for this type of production. Nature-based Solutions: Practices that handle production in a natural way, reducing chemical applications and restoring soil health, such as regenerative agriculture, holistic management, permaculture, agroecology, production of organic food, or natural forestry farms. We include reforestation and afforestation. Also, we include here farming strategies that seek the recovery of carbon credits from sustainable practices. Alternative productions: algae farms in a controlled environment, seaweed production at an industrial scale, insect rearing farms at an industrial scale. Also, we include companies providing feed solutions to aquaculture based on insects or algae.
Lab-based proteins and food ingredients	Lab-based and Cultured Food: Cellular agriculture, lab-grown foods, synthetic biology, cell-based meat and ingredients, precision fermentation technologies, engineered proteins, protein design, seaweed or algae used as a base for precision fermentation processes (mimicking meat and other proteins' taste and quality) Plant-based Proteins: technologies to replace meat, dairy, and seafood products (animal-free alternatives) based on plants (not cultured food or engineered proteins). [More traditional plant-based ingredients not replacing animal proteins and traditional vegan/vegetarian food go into “Functional and healthy foods”]. Molecular technologies: molecular farming, other molecular technologies. Other Lab-based Food Science Tools: food nanotechnology, nanostimulation, and CO_2-based proteins.

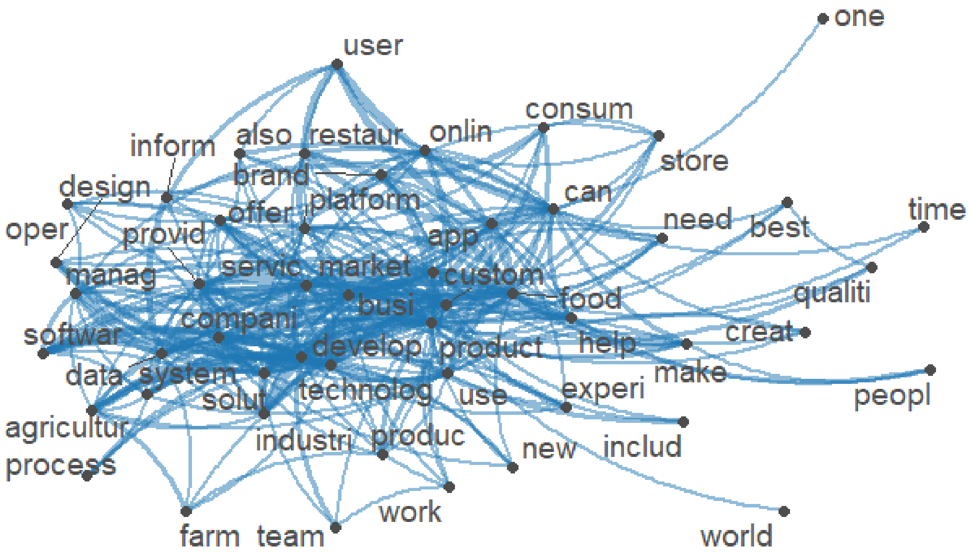
Solution	Details
E-commerce and delivery solutions	e-commerce platforms: e-grocery, e-retail, digital marketplaces for groceries and fresh foods, online shopping, mobile app shopping. Delivery intermediaries and solutions: Last-mile delivery, B2B and B2C delivery solutions, delivery intermediaries, vending machine technologies (does not include autonomous or robot delivery that is in other categories). Digital agribusiness marketplaces: ag input trading platforms, app-based procurement of ag inputs, and apps for buying, hiring, or sharing machinery. We also include here Uber-type tools (like Uber for tractors). Apps connecting farmers to buyers and final consumers: apps seeking to shorten value chains, connecting farmers with buyers and consumers. B2B e-platforms seeking to help large and SME retailers source food products. Apps for fresh food wholesale directly from producers.
Digital food service	Technologies for Restaurants: restaurant management solutions, catering and restaurant automation systems, online and mobile ordering, booking and e-reservation systems, solutions for the hospitality industry, CRM platforms, virtual, cloud & dark kitchen for delivery-only restaurants. Food social networks: restaurant marketplaces, virtual restaurants, food social networks; chef networks, apps to split accounts, customer information apps, customer engagement, food blogging, digital restaurant directory. Personalized foods: services delivering ready-to-eat homemade meals, services delivering custom ingredients to cook pre-defined meals, online recipes; corporate food services, home-cooking kits, apps for home chefs to sell their foods, home-cooked food, meal planning services, meal delivery, home-cooked and pre-cooked meals, food sold by home-chefs, pre-portioned ingredients or meal kit delivery for cooking at home. Cooking & kitchen technologies: Household smart kitchen devices, automation technologies for kitchens, robotics, and IoT applied to cooking devices. Includes other devices for cooking, like 3D printers.
Functional and healthy foods	Functional Foods: nutrient-enhanced foods, nutraceuticals; food designed to improve diseases such as diabetes and other medical conditions, food designed for people with allergies (allergen-free). Improved infant nutrition and baby foods, dietary or nutritional supplements and bioactive components such as probiotics and prebiotics. Healthy and Alternative Food Ingredients: protein supplements and powders; plant-based food (that are not aimed at being perfect substitutes to meat); healthy snacks; organic or non-GMO foods; gluten-free food and ingredients; sustainably-sourced foods; energy foods; nutrient-enhanced and superfoods; ayurvedic supplements or ingredients; healthy food alternative oriented to children; vegan and vegetarian alternative ingredients; sugar-free or sugar-reduced food alternatives; vitamin-infused foods; food with improved nutritional balance; food free of artificial ingredients, colorants or preservatives; hydration solutions; electrolyte drinks; natural cold-pressed juices and drinks; paleo ingredients; seaweed or algae healthy snacks; enriched food and nutritional products based on algae; insect flour and other insect-based products with enriched protein characteristics; tapping water systems to improve water quality. [This category includes vegan/vegetarian and plant-based food that is not aimed at creating meat, egg, or other protein substitutes. These are more generic or traditional foods that are not based on precision or biomass fermentation] [Online marketplaces, apps, or online websites that sell organic, vegan, etc., go in the category of e-commerce] Precision Nutrition: personalized nutritional recommendations; digital health advisory services; education and awareness services; apps for weight reduction; food designed according to personal characteristics; personal health or gut microbiome test to develop specific diets; nutritional health advisory.

Solution	Details
Logistics, food safety, and traceability solutions	Warehousing Solutions: automated and digital warehousing; warehousing rental; robot palletization; robots for merchandise handling. Freight & Transportation Solutions: online freight management; digital shipping carrier solutions; clean transportation technologies; delivery & cargo robots; autonomous vehicles for food delivery and transportation; contactless delivery Food Safety and Preservation Technologies: cold storage; refrigeration; thermal control; automation monitoring; ultrasound; pulsed and ultraviolet light, high-pressure processing technologies (HPP), drying technologies at the farm level; tools to improve post-harvest management; food testing Traceability & Tracking: Blockchain and distributed ledger technologies; verification services; tags; tracking services Food Information: labeling; carbon credits measure & validation, food rating apps, calculation of food GHG emissions; platforms providing information about product attributes; real-time measuring of emissions and pollution; food recognition by image or scanning In-store Solutions for Grocery Stores & Supermarkets: Technology gadgets to brick-and-mortar stores; digital shelf technologies; in-store automation solutions for supermarkets, technologies for the reduction in waiting lines. Self-checkout technologies, frictionless technologies. Digitalized Fulfillment Solutions: micro-fulfillment and micro-retail solutions; tools for the digitalization of the procurement process; B2B sourcing marketplaces and management solutions oriented to SMEs grocery retailers.
Financial solutions for food and agriculture	Digital Payment Services: payment platforms; e-payment; sms payment; cryptocurrencies oriented to food and agriculture; token services; currency management solutions. Fintech Solutions: Digital credit access; credit risk assessment; crowdfunding & crowd farming for farm investment; insurtech solutions. Micro-Financial Solutions for Farmers: apps that support financial inclusion, farmer empowerment, flexible loan programs for rural women farmers or small-scale farms
Waste reduction and cascading uses	Cascading Use of Waste from Agriculture and Industrial Production: Companies using waste from industrial and agricultural operations. This includes bioenergy; bioproducts; biorefineries; microbial proteins from organic waste; alternative uses for food byproducts; environmental remediation services; applications from spent or upcycled materials; feed produced from food waste and other residues; use of insects as natural upcyclers for residues; bioconversion processes; upcycling of food residues into new uses. Food Losses & Waste Reduction: Monitoring of food waste; apps for planning food needs; rescue of 'ugly" or imperfect food; platforms that connect people and businesses to share food that is about to expire and reduce food waste; apps and solutions to reduce food waste at home [Logistics solutions that are oriented to avoid food waste, such as post-harvest technologies, remote control of temperature or cold chain solutions, go in a different category] Packaging Technologies: Alternatives to reduce single-use and fossil-based plastics. Smart packaging. Bioplastics; biodegradable and recyclable packaging sources. Invisible packaging for fruits such as natural and biological coatings; edible coatings; nano-coatings. Water soluble packaging. Biodegradable packaging; reusable packaging.

Appendix 2 2. Classification of the annotated set

Class	n (%)
Not relevant	**2237 (42%)**
Relevant	**3056 (58%)**
Digital food service	551 (18%)
E-commerce and delivery solutions	504 (16%)
Functional and healthy foods	503 (16%)
Precision agriculture, smart farming and farm robotics	365 (12%)
Alternative ways of farming	262 (8.6%)
Logistics food safety and traceability solutions	256 (8.4%)
Waste reduction and cascading uses	205 (6.7%)
Lab-based proteins and food ingredients	174 (5.7%)
Plant, animal and food biotechnology	100 (3.3%)
Financial solutions for food and agriculture	73 (2.4%)
Biological inputs and solutions	63 (2.1%)
Total	**n = 5,293**

Appendix 2 3.Wordcloud and co-occurrence matrix for the most common tokens in the text corpus.



Appendix 2 4. List of incumbent firms considered for the analysis.

investor_name	sector
Leaps by Bayer	agrochemicals_and_seeds
Bayer	agrochemicals_and_seeds
BASF	agrochemicals_and_seeds
BASF Venture Capital	agrochemicals_and_seeds
UPL	agrochemicals_and_seeds
UPL	agrochemicals_and_seeds
FMC Ventures	agrochemicals_and_seeds
Sumitomo Chemical	agrochemicals_and_seeds
Sumitomo Corporation	agrochemicals_and_seeds
Sumitomo Corporation Equity Asia	agrochemicals_and_seeds
Sumitomo Corporation Europe Limited	agrochemicals_and_seeds
Nufarm	agrochemicals_and_seeds
Bayer Pharmaceuticals	agrochemicals_and_seeds
Syngenta Ventures	agrochemicals_and_seeds
Syngenta	agrochemicals_and_seeds
Syngenta Group	agrochemicals_and_seeds
Yara Growth Ventures	synthetic_fertilizers
Yara International	synthetic_fertilizers
Nutrien Ag Solutions	synthetic_fertilizers
ICL Group	synthetic_fertilizers
ICL Planet Startup Hub	synthetic_fertilizers
EuroChem Group AG	synthetic_fertilizers
K+S Group	synthetic_fertilizers
John Deere	farm_machinery
CLAAS	farm_machinery
AGCO	farm_machinery
KUBOTA Corporation.	farm_machinery
Kubota	farm_machinery
Mahindra Agri Solutions	farm_machinery
Cargill	commodity_trading
Cargill Ventures	commodity_trading
Louis Dreyfus	commodity_trading
Louis Dreyfus Company	commodity_trading
Bunge	commodity_trading
Bunge Ventures	commodity_trading
COFCO	commodity_trading
ADM Venture Capital	commodity_trading
ADM Ventures	commodity_trading
ITOCHU Corporation	commodity_trading
Itochu-Shokuhin	commodity_trading
Marubeni	commodity_trading
Archer Daniels Midland Company	commodity_trading
PepsiCo	food_and_beverage
Nestlé	food_and_beverage
Nestlé Health Science	food_and_beverage

Anheuser-Busch InBev	food_and_beverage
Tyson Foods	meat_and_protein
Tyson Ventures	meat_and_protein
Mars	food_and_beverage
The Coca-Cola Company	food_and_beverage
Coca-Cola Enterprises	food_and_beverage
Coca-Cola Venturing & Emerging Brands	food_and_beverage
Coca-Cola Amatil	food_and_beverage
Danone	food_and_beverage
Danone Manifesto Venture	food_and_beverage
Mondelez International	food_and_beverage
The Kraft Group	food_and_beverage
BRF	meat_and_protein
NH Foods	meat_and_protein
Marfrig	meat_and_protein
Charoen Pokphand Group	seafood
Trident	seafood
Thai Union Group	seafood
Walmart	grocery_retail
Walmart Foundation	grocery_retail
Kroger	grocery_retail
Kroger Co. Zero Hunger	grocery_retail
ALDI	grocery_retail
Carrefour	grocery_retail
Rewe Group	grocery_retail
Ahold Delhaize	grocery_retail
Tesco	grocery_retail
Merck Animal Health	animal_pharma
Merck Animal Health Ventures	animal_pharma
Novartis	animal_pharma
Elanco	animal_pharma
Nutreco	animal_pharma

Sources:

etc Group (2022) Food Barons 2022: Crisis Profiteering, Digitalization and Shifting Power.

IPES-Food (2017). Too big to feed: The short report. Mega-mergers and the concentration of power in the agri-food sector: How dominant firms have become too big to feed humanity sustainably.

Appendix 2 5. Summary of the performance measures for ML models.

In addition to the three algorithms that were finally selected as the best performing (i.e., NB, SVM, and LASSO plus topics from the LDA analysis), we also tried other more sophisticated algorithms.

We run the Random Forest (RF) algorithm using the randomForest package. RF models create random decision trees based on a bootstrapping approach. The problem with this type of algorithm is that they present high demands regarding computational resources, especially with a high number of trees.

For the binary classification problem, we also explore more complex deep learning algorithms. These neural-based algorithms are built over word embeddings, considering the context in which a word is used for classification. Instead of using the bag-of-word approach, they take advantage of the order of the words in a text corpus based on a multi-layer approach. The general architecture of these neural-based algorithms starts with an input layer (which can be, for example, features of a TF-IDF matrix or a sequence of word embeddings), then we have several hidden layers that capture the relationship between words and information on the structure of the sentences, and finally, we have an output layer that is our set of target categories. In the process, each layer receives information from a previous layer and passes that information to the next one. We apply the simple and convoluted neural network algorithms using the package tidymodels. Although these are more complex models, they need substantial data to perform well (which is not our case since we are working with a relatively small dataset).

Finally, for the multiclass problem, we also try a seeded LDA approach, which is a semi-supervised technique that works similarly to topic models, but the researcher has to pre-define the number of topics and feed the algorithms with keywords associated with that topic.

The results for all these algorithms are summarized in the following two tables:

Binary Stage	**NB**	**SVM**	**LASSO**	**LASSO + Topics LDA**	**LASSO + Topics LDA + Hyperparam**	**RF**	**Simple Neural Network**	**Convolutional Neural Network (CNN)**
	quanteda	*quanteda*	*tidymodels*	*tidymodels*	*tidymodels*	*randomForest*	*tidymodels*	*tidymodels*
Accuracy	0.806	0.795	0.774	0.776	0.760	0.765	0.733	0.673
ROC AUC	0.787	0.783	0.843	0.856	0.836	0.758	0.813	0.814
Precision (rate of true positives)	0.911	0.797	0.768	0.781	0.772	0.901	0.714	0.643
Neg. Pred Value (rate of true negatives)	0.663	0.792	0.786	0.767	0.740	0.614	0.711	0.870

Base: 5293 companies in the labelled dataset
Null model: Accuracy=0.57; ROC AUC = 0.5

Multiclass problem	**NB**	**SVM**	**LASSO**	**LASSO + Topics LDA**	**LASSO + Topics LDA + Hyperparam**	**RF**	**Seeded LDA**
	quanteda	*quanteda*	*tidymodels*	*tidymodels*	*tidymodels*	*randomForest*	*quanteda*
Accuracy	0.731	0.750	0.732	0.753	0.729	0.658	0.553
ROC AUC	0.784	0.803	0.947	0.955	0.946	0.720	0.748

Base: 3056 companies labelled as relevant in the original dataset
Null model: Accuracy=0.16; ROC AUC = 0.5

Appendix 2 6. A detailed list of investment strategies by incumbent firms.

Strategy	Investor	Target Sector
Upgrading strategies	Farm machinery	Precision agriculture and smart farming
	Agrochemicals and Seeds Synthetic Fertilizers	Precision agriculture and smart farming
	Agrochemicals and Seeds Synthetic Fertilizers Veterinary Pharma	Plant Biotechnology
	Food & Beverage	Functional foods
	Food & Beverage	Waste reduction
	Grocery Retail Commodity Trading	Logistics, food safety & traceability solutions
	Commodity Trading Agrochemicals and Seeds Synthetic Fertilizers Farm Machinery	E-commerce (agribusiness marketplaces)
	Grocery Retail	E-commerce
Adaptation or Control Strategies	Meat and Protein Seafood Food & Beverage Animal Pharma	Cellular agriculture and plant-based
	Agrochemicals and Seeds Synthetic Fertilizers	Biological inputs
	Commodity Trading	Alternative ways of farming
	Agrochemicals and Seeds Synthetic Fertilizers Commodity Trading	Financial solutions for food & agriculture
Opportunity Strategies	Commodity Trading	Cellular agriculture and plant-based
	Commodity Trading	Biological inputs
	Commodity Trading	Precision agriculture and smart farming
	Commodity Trading	Plant biotechnology
	Grocery Retail	Alternative ways of farming
	Food & Beverage	E-commerce
	Food & Beverage	Digital food service

Appendix Chapter 3

Appendix 3 1. Systematization of the literature

Paper	Period	Geographical Scope	Outcome variable	Methods	Control for Institutional or macro-level instability	Include AUC	Subsampling
Shrimali and Kniefel (2011)	1991–2007	50 US States	RE capacity / Total net generation (%)	TWFE	N	N	-
Gan and Smith (2011)	1994–2003	26 OECD countries	RE supply (per cápita)	TWFE	N	N	-
Marques and Fuinhas (2012)	1990–2007	23 EU countries	RE over total primary energy supply (%)	PCSE, RE, TWFE	N	N	-
Dong (2012)	2005–2009	53 countries	Wind cumulative and total capacity	OLS, TWFE, RE	N	N	-
Jenner et al. (2013)	1992–2008	26 EU countries	RE annual added capacity	FE	N	Y (+/-)	-
Zhao et al. (2013)	1980–2010	122 countries	RE over total electricity generation (%)	OLS, PPML	N	N	Developed / Developing / Emerging countries
Aguirre and Ibikunle (2014)	1990–2010	38 countries (all EU, rest of OECD countries and Brazil, Russia, India, China and SA)	RE over total primary energy supply (%)	FEVD, PCSE	N	N	-
Flora et al. (2014)	1998–2011	18 European countries	RE unused output to maximum possible output (%)	OLS, RE, FE, AR(1)	N	N	-
Omri (2015)	1990–2011	64 countries	RE consumption	Pooled, TWFE, RE diff-GMM, sys-GMM	N	N	High / Middle / Low Income countries
Sisodia and Soares (2015)	1995–2011	European Union (EU-27)	RE Investments (solar and wind)	OLS	N	N	-
Polzin et al. (2015)	2000–2011	30 countries (mostly OECD)	RE annual added capacity	OLS, TWFE, RE	N	N	-
Kilinc-Ata (2016)	1990–2008	27 EU countries and 50 US states	RE capacity over total capacity (%)	TWFE	N	Y (+)	-
Cadoret and Padovano (2016)	2004–2011	26 European countries	RE in gross energy consumption (%)	LSDV (1st stage) + OLS (2nd stage)	Y (corruption)	N	-
Sisodia et al. (2016)	1995–2011	27 European countries	RE Investments (solar and wind)	OLS	Y (regulatory quality)	N	EU 27 / EU-15 / EU-11
Romano et al. (2017)	2004–2013	56 countries	RE generation over total net electricity generation (%)	OLS, RE, FE	N	N	Developed / Developing countries
Upton and Snyder (2017)	1990–2013	49 US States	RE supply (per cápita)	SC	N	N	-
Ramalho et al. (2018)	1971–2004	193 countries	RE contribution to electricity output (in GWh)	Multinomial fractional Logit	Y (democratization)	N	-
Sequeira and Santos (2018)	1998–2017	Between 100 and 126 countries (meta-analysis)	RE in gross energy consumption (%)	Multinomial fractional Probit	Y (democratization)	N	-
Liu et al (2019)	2000–2015	29 countries (all EU, rest of OECD, Kyoto Protocol signees + India and China)	RE total installed capacity	RE, FE	N	N	-
Damette and Marques (2019)	1990–2012	24 Eropean countries	RE share over total energy production (%)	Fully Modified OLS Dynamic OLS	N	N	-
Bento et al. (2020)	2004–2014	20 OECD countries	RE capacity yearly increase	OLS, PSM, SC	N	Y (+)	-
Marques et a.l (2010)	1990–2006	24 EU countries	RE contribution to energy supply (%)	OLS, FE, RE, FEVD	N	N	-
Bersalli et al. (2020)	1995–2015	20 Latin american countries and 30 European countries	RE added capacity	FE, RE	N	Y (+)	European / Latin American countries
Uzar (2020)	1990–2015	32 Countries	RE consumption	ARDL	Y (institutional quality)	N	-
Kersey (2021)	2000–2018	31 Caribbean islands	RE cumulative capacity	TWFE	N	N	-
Abban and Hasan (2021)	2007–2017	60 countries	RE added capacity	sys-GMM	N	N	Developed / Developing countries
Hille and Oelker (2023)	2005–2018	189 countries	RE capacity	TWFE	N	Y (+)	-

TWFE = two-way fixed effects; **FE** = fixed effects; **RE** = random effects; **OLS** = Ordinary least squared; **SC** = Synthetic Control; **LSDV** = Least Square Dummy Variable;
PPML = Poisson pseudo-maximum likelihood; **diff-GMM** = difference generalized method of moments; **sys-GMM** = system generalized method of moments;
PCSE = Panel Corrected Standard Error; **FEVD** = Fixed Effects Vector Decomposition; **PSM** = Propensity Score Matching
AR (1) = Autorregressive model of order 1; **ARDL** = Autoregressive distributed lag model

Appendix 3 2. Start year of the auction program by country

Country	ISO	Treatment start	Sources
Estonia	EST	2020	AURES II
Ukraine	UKR	2020	Del Río and Kiefer (2021)
Croatia	HRV	2019	AURES II - Del Río and Kiefer (2021)
Hungary	HUN	2019	AURES II - Del Río and Kiefer (2021)
Slovakia	SVK	2019	AURES II
Colombia	COL	2019	Matthäus (2020) - Del Río and Kiefer (2021)
Bahrain	BHR	2019	Matthäus (2020) - IRENA (2019)
Cambodia	KHM	2019	Del Río and Kiefer (2021)
Ecuador	ECU	2019	Del Río and Kiefer (2021)
Finland	FIN	2018	AURES II
Luxembourg	LUX	2018	AURES II - Del Río and Kiefer (2021)
Senegal	SEN	2018	Matthäus (2020) - Del Río and Kiefer (2021)
Kuwait	KWT	2018	Matthäus (2020) - IRENA (2019)
Oman	OMN	2018	Matthäus (2020) - IRENA (2019)
Qatar	QAT	2018	Matthäus (2020) - IRENA (2019)
Albania	ALB	2018	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2019)
Kazakhstan	KAZ	2018	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2019)
Philippines	PHL	2018	IRENA (2019)
Tunisia	TUN	2018	Del Río and Kiefer (2021) - IRENA (2019)
Madagascar	MDG	2018	Del Río and Kiefer (2021) - IRENA (2019)
Slovenia	SVN	2017	AURES II - Matthäus (2020)
Ethiopia	ETH	2017	Matthäus (2020) - Del Río and Kiefer (2021)
Saudi Arabia	SAU	2017	Matthäus (2020) - Del Río and Kiefer (2021) - Krueger (2018)
Turkey	TUR	2017	Matthäus (2020) - Del Río and Kiefer (2021)
Algeria	DZA	2017	Del Río and Kiefer (2021) - IRENA (2019)
Armenia	ARM	2017	Del Río and Kiefer (2021) - IRENA (2019)
Japan	JPN	2017	Del Río and Kiefer (2021) - IRENA (2019)
Israel	ISR	2017	Del Río and Kiefer (2021) - IRENA (2019)
Namibia	NAM	2017	Del Río and Kiefer (2021) - IRENA (2019)
Lebanon	LBN	2017	Del Río and Kiefer (2021) - IRENA (2019)
Bangladesh	BGD	2017	IRENA (2019)
Argentina	ARG	2016	Del Río and Kiefer (2021) - Viscidi and Yepez (2019)
Greece	GRC	2016	AURES II - Del Río and Kiefer (2021)
Poland	POL	2016	AURES II - Matthäus (2020) - Del Río and Kiefer (2021)
Spain	ESP	2016	AURES II - Del Río and Kiefer (2021)
Jamaica	JAM	2016	Del Río and Kiefer (2021) - Viscidi and Yepez (2019)
Mexico	MEX	2016	Matthäus (2020) - Del Río and Kiefer (2021) - Krueger (2018)
Zambia	ZMB	2016	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2018)
Thailand	THA	2016	Del Río and Kiefer (2021) - IRENA (2019)
Sri Lanka	LKA	2016	Del Río and Kiefer (2021) - IRENA (2019)
Malaysia	MYS	2016	Del Río and Kiefer (2021)
Germany	DEU	2015	AURES II - Del Río and Kiefer (2021)
Chile	CHL	2015	Matthäus (2020) - Del Río and Kiefer (2021) - Viscidi and Yepez (2019)
Uganda	UGA	2015	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2018)
Ghana	GHA	2015	Del Río and Kiefer (2021)
Egypt	EGY	2014	Del Río and Kiefer (2021)
Lithuania	LTU	2013	AURES II - Matthäus (2020)
El Salvador	SLV	2013	Matthäus (2020) - Del Río and Kiefer (2021)
Indonesia	IDN	2013	Del Río and Kiefer (2021)
Jordan	JOR	2013	Del Río and Kiefer (2021)
Russia Federation	RUS	2013	Del Río and Kiefer (2021)
France	FRA	2012	AURES II - Del Río and Kiefer (2021)
Italy	ITA	2012	AURES II - Del Río and Kiefer (2021)
Australia	AUS	2012	Matthäus (2020) - Del Río and Kiefer (2021)
United Arab Emirates	ARE	2012	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2018)
Netherlands	NLD	2011	AURES II - Matthäus (2020) - Del Río and Kiefer (2021)
United States	USA	2011	Matthäus (2020) - Del Río and Kiefer (2021)
Panama	PAN	2011	Matthäus (2020) - Del Río and Kiefer (2021)
South Africa	ZAF	2011	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2018)
Guatemala	GTM	2011	Matthäus (2020)
Honduras	HND	2011	IRENA (2013)
Morocco	MAR	2011	Del Río and Kiefer (2021) - Krueger (2018)
India	IND	2010	Del Río and Kiefer (2021) - Krueger (2018)
Peru	PER	2009	Del Río and Kiefer (2021) - Krueger (2018) - IRENA (2013)
Brazil	BRA	2007	Del Río and Kiefer (2021) - Krueger (2018) - Viscidi and Yepez (2019) - IRENA (2013)
Portugal	PRT	2006	AURES II - Matthäus (2020) - Del Río and Kiefer (2021)
Uruguay	URY	2006	Matthäus (2020) - Del Río and Kiefer (2021)
Denmark	DNK	2005	AURES II - Matthäus (2020) - Del Río and Kiefer (2021)
Canada	CAN	2005	Del Río and Kiefer (2021)
China	CHN	2003	Del Río and Kiefer (2021) - Matthäus (2020) - IRENA (2013)
Cyprus	CYP	0	
Costa Rica	CRI	0	
Bolivia	BOL	0	
Rwanda	RWA	0	
Tanzania	TZA	0	
Paraguay	PRY	0	
Austria	AUT	0	
Belgium	BEL	0	
Czechia	CZE	0	
Iceland	ISL	0	
Korea, Republic of	KOR	0	
Latvia	LVA	0	
Mauritius	MUS	0	
New Zealand	NZL	0	
Norway	NOR	0	
Sweden	SWE	0	
Switzerland	CHE	0	
Belarus	BLR	0	
Bosnia and Herzegovina	BIH	0	
Bulgaria	BGR	0	
Dominican Republic	DOM	0	
Iran, Islamic Republic of	IRN	0	
Macedonia	MKD	0	
Kenya	KEN	0	
Moldova, Republic of	MDA	0	
Mongolia	MNG	0	
Nicaragua	NIC	0	
Ivory Coast	CIV	0	
Ireland (*)	*IRL*	*Before 2000*	*Del Río and Kiefer (2021)*
United Kingdom (*)	*GBR*	*Before 2000*	*Del Río and Kiefer (2021)*

(*) Removed from the analysis

Sources:

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del Río, P., Kiefer, C.P., 2021. Analysing patterns and trends in auctions for renewable electricity. Energy for Sustainable Development, 62, 195–213. https://doi.org/10.1016/j.esd.2021.03.002

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Matthäus, D., 2020. Designing effective auctions for renewable energy support. Energy Policy, 142, 111462. https://doi.org/10.1016/j.enpol.2020.111462 *[Supplementary material provided by the author]*

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Appendix 3 3. Results for alternative specifications. Determinants of treatment adoption (Poisson models)

We present alternative specifications of the Poisson models to determine self-selection in the treatment adoption. In each specification, we gradually added different groups of covariates (as defined in Section 3.4). The six variables from the Worldwide Governance Indicators database included in the vector INS_i^{2000} were added separately to avoid multicollinearity.

The results were consistently significant for the macroeconomic variables across models for FDI and inflation. The rule of law is the only significant variable from the institutional setting.

In the main text, we present model 6, which performs best according to the deviance and the Akaike information criteria.

	Dep. Var.: Lenght of treatment (number of years with auctions in the period 2000-2020)									
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Share of wind, solar and biomass	0.127*	0.123*	0.216***	0.162**	0.175*	0.228***	0.222**	0.226*	0.176***	0.183*
	(0.074)	*(0.066)*	*(0.061)*	*(0.081)*	*(0.099)*	*(0.068)*	*(0.109)*	*(0.124)*	*(0.062)*	*(0.095)*
Feed-in policies	3.100**	2.912**	2.579	2.113	2.006	1.889	1.497	1.684	2.032	2.308
	(1.288)	*(1.355)*	*(1.642)*	*(1.417)*	*(1.346)*	*(1.701)*	*(1.095)*	*(1.286)*	*(1.609)*	*(1.545)*
share fo electricity from fossil sources		0.002	−0.016	−0.008	−0.01	−0.016	−0.014	−0.017	−0.011	−0.013
		(0.023)	*(0.018)*	*(0.020)*	*(0.017)*	*(0.015)*	*(0.016)*	*(0.012)*	*(0.021)*	*(0.015)*
Oil rents		-0.015	−0.072***	−0.047**	−0.058**	−0.081***	−0.073**	−0.060**	−0.048***	−0.084*
		(0.030)	*(0.022)*	*(0.021)*	*(0.029)*	*(0.026)*	*(0.036)*	*(0.027)*	*(0.016)*	*(0.051)*
CO2 emissions per capita		0.124	0.776*	0.268	0.356*	0.471	0.499	0.427*	0.345*	0.424*
		(0.271)	*(0.403)*	*(0.182)*	*(0.190)*	*(0.296)*	*(0.308)*	*(0.229)*	*(0.198)*	*(0.225)*
Net imports of electricity		-0.002	-0.008	-0.01	-0.008	-0.011	-0.01	-0.006	-0.007	-0.008
		(0.051)	*(0.044)*	*(0.048)*	*(0.045)*	*(0.044)*	*(0.048)*	*(0.044)*	*(0.050)*	*(0.046)*
Solar potential			1.286***	1.223**	1.229**	1.225***	1.173**	1.207***	1.199**	1.132**
			(0.339)	*(0.529)*	*(0.521)*	*(0.350)*	*(0.462)*	*(0.448)*	*(0.510)*	*(0.568)*
Wind potential			-0.049	0.006	0.04	0.460*	0.146	0.258	0.07	0.111
			(0.351)	*(0.229)*	*(0.219)*	*(0.235)*	*(0.209)*	*(0.224)*	*(0.172)*	*(0.196)*
Biomass potential			−0.006***	−0.004***	−0.004***	−0.005**	−0.004***	−0.004***	−0.004***	−0.003
			(0.001)	*(0.001)*	*(0.001)*	*(0.002)*	*(0.001)*	*(0.002)*	*(0.001)*	*(0.002)*
FDI				0.043***	0.048***	0.104***	0.080***	0.074**	0.047***	0.056***
				(0.005)	*(0.010)*	*(0.016)*	*(0.026)*	*(0.029)*	*(0.008)*	*(0.020)*
Inflation				−0.055**	−0.058**	−0.070***	−0.064**	−0.061**	−0.055**	−0.056**
				(0.025)	*(0.027)*	*(0.023)*	*(0.028)*	*(0.028)*	*(0.022)*	*(0.024)*
Currency crisis				4.082	4.27	6.467*	4.828	4.627	4.07	4.598
				(3.203)	*(3.356)*	*(3.914)*	*(3.655)*	*(3.488)*	*(3.080)*	*(3.544)*
Debt crisis				0.509	0.464	−0.334	0.023	0.114	0.421	0.237
				(1.958)	*(1.939)*	*(1.943)*	*(1.905)*	*(1.940)*	*(1.986)*	*(1.928)*
Regulatory quality					−0.015					
					(0.026)					
Rule of law						−0.093***				
						(0.025)				
Government effectiveness							−0.06			
							(0.041)			
Control of corruption								−0.052		
								(0.047)		
Political stability and no violence									−0.015	
									(0.016)	
Voice and accountability										−0.039
										(0.057)
Num. obs.	98	98	98	98	98	98	98	98	98	98
Deviance	424.88	423.93	394.86	372.57	372.19	350.49	366.55	366.14	371.73	367.65
AIC	676.42	683.47	660.41	646.12	647.74	626.03	642.09	641.69	647.28	643.20

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

(Standard errors)

Errors clustered by Income Group Year 2000 (WB)

Appendix 3 4. Cluster and principal component analysis (PCA)

As presented in Section 3.4, we use 10 variables to characterize the business environment (comprising macroeconomic stability and institutional quality). To classify countries according to the quality of their business environment, we combine two methodologies—PCA and cluster analysis—both of which belong to the unsupervised learning field and aim to reduce the number of dimensions in a multivariate dataset. Cluster analysis finds specific groups within the data and classifies observations according to such groups, whereas PCA identifies the main sources of variability within a dataset, helping to keep only a few components from a high-dimensional dataset.

We calculated averages for the period under analysis for the variables that belong to the vectors ECO_{it} and INS_{it} and standardized them (this implied dropping the panel feature of the data). Thus, the following variables were used in both analyses:

- The average financial development index (FDI) 2000–2019
- The average annual rates of inflation 2000–2020
- Number of currency crises 2000–2019
- Number of debt crises 2000–2019
- The average index of Regulatory Quality (rqe) 2000–2020
- The average index of Government Effectiveness (gee) 2000–2020
- The average index of Rule of Law (rle) 2000–2020
- The average index of Control of Corruption (cce) 2000–2020
- The average index of Political Stability and No Violence (pve) 2000–2020
- The average index of Voice and Accountability (vae) 2000–2020

We start with a **PCA analysis.** The goal is to work with a more manageable number of components that explain most of the variability. We use the function "princomp'"from the R package stats.

As shown in the following table, the first three components explain approximately 87% of the variability in the data. Therefore, we use these three components as the basis for our analysis.

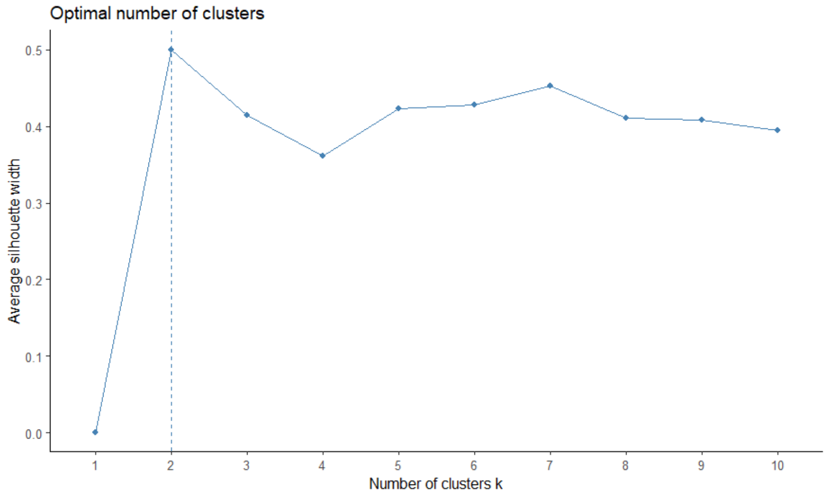
	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10
standard deviation	2.563	1.176	0.876	0.650	0.562	0.524	0.396	0.249	0.158	0.151
proportion of variance	0.657	0.138	0.077	0.042	0.032	0.027	0.016	0.006	0.002	0.002
cumulative proportion	0.657	0.795	0.872	0.914	0.946	0.973	0.989	0.995	0.998	1.000

We extract the scores for the first three components. Then, for illustrative purposes, we present the first 10 components (out of the total 98) in the following table.

n	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10
1	4.346	0.523	0.037	0.757	0.145	-0.310	0.302	-0.079	0.095	0.259
2	3.908	0.381	-0.255	-0.101	0.145	-0.140	-0.195	0.064	-0.201	-0.047
3	0.042	-1.184	0.571	0.656	0.690	0.592	-0.732	-0.358	-0.105	0.120
4	3.348	0.175	-0.107	0.123	-0.134	-0.225	-0.031	0.099	0.032	-0.184
5	4.384	0.477	-0.076	0.547	0.122	-0.212	0.206	0.033	0.092	0.066
6	2.589	0.084	-0.107	-0.265	-0.050	-0.329	-0.551	-0.138	0.044	0.193
7	0.769	-0.551	0.055	-0.451	-0.146	0.371	0.530	0.034	0.059	-0.212
8	2.368	-0.152	-0.218	0.066	-0.237	-0.052	-0.105	-0.093	0.034	-0.137
9	1.974	-0.142	-0.226	-0.739	-0.145	0.191	0.129	-0.363	-0.279	-0.110
10	4.570	0.512	-0.306	0.074	0.142	-0.293	-0.500	0.168	0.177	-0.078
…	…	…	…	…	…	…	…	…	…	…

We move to the cluster analysis by taking these first three scores. In this case, we use the partitioning around medoids (k-medoids) approach, which is less sensitive to noise and outliers than the traditional k-means approach, providing more robust results (Kassambara, 2017). The k-medoids approach search for representative data points within the data (called “medoids”). The rest of the data points are assigned to each cluster according to their proximity to these medoids using Euclidean or Manhattan distance measures (Kaufman & Rousseeuw, 1990). The representative data points are the center of the k-clusters.

We use the R packages factoextra (Kassambara & Mundt, 2020) and cluster (Maechler et al., 2022). Because the number of clusters must be predefined, we base our decision on the silhouette graph[32]. As shown in the following chart, the optimal number of clusters in our data is two:



With this analysis, we obtain two different groups in terms of the medians, as can be seen in the following table[33]:

Variable	Low quality (n = 58)	High quality (n = 40)	p-value (1)
average rqe	−0.20 (0.44)	1.13 (0.43)	<0.001
average rle	−0.43 (0.40)	1.12 (0.54)	<0.001
average cce	−0.48 (0.37)	1.08 (0.72)	<0.001
average gee	−0.29 (0.37)	1.18 (0.52)	<0.001
average pve	−0.44 (0.55)	0.86 (0.47)	<0.001
average vae	−0.30 (0.59)	1.07 (0.59)	<0.001
average FDI	0.23 (0.14)	0.59 (0.21)	<0.001
average Inflation	6.1 (5.0)	2.1 (1.5)	<0.001
number of debt crisis	1.0 (6.4)	0.0 (0.5)	<0.001
number of currency crisis	0.0 (1.66)	0.0 (0.27)	0.002

Median (SD)

(1) Wilcoxon rank sum test

As presented in the following table, 68% in the high-quality group and 74% in the low-quality group adopted auctions during the period under analysis. This means that the control is reasonably large in both subsamples.

[32] The silhouette is a measure of closeness of the datapoints within a cluster. A higher silhouette value reflects a better quality of the cluster analysis.

[33] The number of debt and currency crises are treated as continuous variables for this purpose.

group	performed_auctions N	Y	Total
High quality	13 (32%)	27 (68%)	40 (100%)
Low quality	15 (26%)	43 (74%)	58 (100%)
Total	28 (29%)	70 (71%)	98 (100%)

Alternative approach: Building an index based on PCA scores

As a robustness check, we use an alternative approach to classify countries according to the quality of their business environment. We built an index using the same first three components we extracted in the cluster analysis. We used the amount of variance explained by each of the first three components to weight the scores for each observation:

$$instindex_i = Scores_{comp1i} \times \frac{var_{comp1}}{(var_{comp1} + var_{comp2} + var_{comp3})} + Scores_{comp2i} \times \frac{var_{comp2}}{(var_{comp1} + var_{comp2} + var_{comp3})} + Scores_{comp3i} \times \frac{var_{comp3}}{(var_{comp1} + var_{comp2} + var_{comp3})}$$

The following table summarizes the main descriptive statistics for the index:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
−3.101	−1.629	−0.506	0.000	1.408	3.763

Finally, we used the mean as a cutoff point to create two groups: every observation with an index above the mean is considered “high-quality,” whereas those below the mean are considered “low-quality.” According to this new approach, 70% adopters are in the high-quality group and 73% in the “low-quality” group, as is shown in the following table. This means we have enough control units in each case.

Group	performed_auctions N	Y	Total
High quality	13 (30%)	30 (70%)	43 (100%)
Low quality	15 (27%)	40 (73%)	55 (100%)
Total	28 (29%)	70 (71%)	98 (100%)

Appendix 3 5. Classification of countries according to the stability of their business environment (PCA and cluster analysis)

	PCA and cluster analysis	
group	**Low quality**	**High quality**
countries	BHR, KWT, PAN, SAU, ALB, ARG, ARM, BLR, BIH, BRA, BGR, CHN, COL, DOM, ECU, GTM, IDN, IRN, JAM, JOR, KAZ, LBN, MKD, MEX, PRY, PER, RUS, THA, TUR, DZA, BGD, BOL, KHM, CIV, EGY, SLV, GHA, HND, IND, KEN, MDA, MNG, MAR, NIC, PHL, SEN, LKA, TZA, TUN, UKR, ZMB, ETH, MDG, RWA, UGA, NAM, ZAF, OMN	AUS, AUT, BEL, CAN, CHL, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, ISL, ISR, ITA, JPN, JOR, LVA, LTU, LUC, MUS, NLD, NZL, NOR, POL, PRT, QAT, SVK, SVN, ESP, SWE, CHE, ARE, USA, URY, MYS, HRV, CRI

	Alternative PCA index	
group	**Low quality**	**High quality**
countries	BHR, KWT, PAN, SAU, ALB, ARG, ARM, BLR, BIH, BRA, BGR, CHN, COL, DOM, ECU, GTM, IDN, IRN, JAM, JOR, KAZ, LBN, MKD, MEX, PRY, PER, RUS, THA, TUR, DZA, BGD, BOL, KHM, CIV, EGY, SLV, GHA, HND, IND, KEN, MDA, MNG, MAR, NIC, PHL, SEN, LKA, TZA, TUN, UKR, ZMB, ETH, MDG, RWA, UGA	AUS, AUT, BEL, CAN, CHL, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, ISL, ISR, ITA, JPN, JOR, LVA, LTU, LUC, MUS, NLD, NZL, NOR, POL, PRT, QAT, SVK, SVN, ESP, SWE, CHE, ARE, USA, URY, MYS, HRV, OMN, CRI, NAM, ZAF

Appendix 3 6. Adoption of the treatment. Cohort (G) composition

G	n	percent
2003	1	1.4%
2005	2	2.9%
2006	2	2.9%
2007	1	1.4%
2009	1	1.4%
2010	1	1.4%
2011	7	10.0%
2012	4	5.7%
2013	5	7.1%
2014	1	1.4%
2015	4	5.7%
2016	10	14.3%
2017	11	15.7%
2018	11	15.7%
2019	7	10.0%
2020	2	2.9%
Treated	70	
Untreated (G=0)	28	

G = year in which the treatment starts

n = number of countries

Appendix 3 7. Results from an alternative subsampling procedure (based on an index using PCA scores)