UNIVERSITAT DE BARCELONA

Essays on Redistribution

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PhD in Economics

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Moltes gràcies a tots, de tot cor.

Contents

1. Introduction

Designing policies and institutions promoting a more equitable and welfare-enhancing distribution of resources stands as one of the principal challenges faced by modern societies. Free market forces embed feedback loops exacerbating income and wealth concentrations. As power and wealth self-reinforce, large levels of inequality go hand in hand with increases in the polarization and heterogeneity of societies. Inequality is not only relevant from a social justice point of view. Economic inequality is deeply entangled with other types of inequality, having negative implications beyond individual outcomes and harming social cohesion, political stability, and economic growth.

Inequality, while an inherent aspect of societies throughout history, is significantly influenced by the design of social structures and economic systems. Proactive measures such as market regulation, the implementation of redistributive policies, the design of institutions, or expansions of the welfare state have the potential to reshape systems and enhance social welfare. The equity-efficiency trade-offs embedded in these policies are by no means a new concept. Yet, as we continue to think on how to implement measures enhancing social welfare, it is crucial to create space for debate and generate the best available evidence that can guide specific policy recommendations.

This dissertation contributes to this debate by studying redistribution from three different perspectives. The second and third chapters explore redistribution from a demand and supply approach, respectively. Focusing on the demand side, the second chapter studies how economic uncertainty induced by labor market institutions affects redistribution demand. More specifically, this chapter analyzes the impact of labor market risk associated with temporary contracts on individual preferences for income redistribution. Focusing on the supply side, the third chapter analyzes redistribution from a tax-design perspective. This chapter documents how the decentralization of the Personal Income Tax to the sub-national level affects its redistributive effect. The fourth chapter takes a different perspective and explores regional differences focusing on the costs and benefits associated with the transition to a clean energy production system. This chapter studies the effect of wind farm development on municipal finances and local tax responses and sheds new light to the ongoing debate on the design of mechanisms facilitating the development of renewable energies by mitigating its geographically concentrated costs.

The characteristics of the Spanish labor market, tax system, and energy sector make the country an ideal setting to perform each of the studies outlined above. In 1984, the liberalization of the use of temporary contracts created segments of workers facing very different degrees of labor security depending on their contract type. The extensive use of temporary contracts derived in one-third of workers subject to this contractual figure and positioned Spain as the European country with the strongest labor market dualization. This strong labor market segmentation offers an interesting context to identify variation on redistribution preferences based on workers' labor market positions. The regional composition of Spain offers an ideal set-up to analyze whether the decentralization of tax instruments leads regions to use their normative power to adapt to their pre-existing characteristics and modify the level of redistribution achieved in their territory. Spain's 17 autonomous communities are characterized by significant heterogeneity in terms of spending needs, political ideology, redistribution preferences, income inequality, labor, and socio-demographic characteristics. Last, Spain's energy sector has undertaken a significant transformation by expanding the production of renewable energy. From 2000 to 2013, its wind energy sector experienced a rapid growth, positioning the country as the second-largest European country in installed wind capacity. The significant expansion of this sector, combined with the lack of specific compensation mechanisms, allows for the study of the financial effect that this type of energy infrastructure has on receiving municipalities.

The second chapter explores the determinants of individual preferences for income redistribution. Basic theory on redistribution demand predicts that increases in inequality should lead to stronger redistribution preferences (Meltzer and Richard, 1981). Yet, this relationship is not always satisfied. Individual's income and its expected variability, interpersonal preferences, beliefs, and values have been identified as determinants of social policy attitudes and help explain why increases in inequality do not directly translate into increases in redistribution demand (Rehm, 2009). Research taking into account labor market divides offers an alternative story by building on the notion that the redistributive function of the public sector can be perceived both as a mechanism to counteract income inequality as well as a form of public insurance against potential income loss (Anderson and Pontusson, 2007; Cusack et al., 2006; Rehm et al., 2012).

Not only do market forces increase differences amongst societies, institutions also play a role. Labor market policies have direct implications for widening or reducing distances between population groups. Although policies introducing flexibility in the labor market aim to promote employment creation by reducing employer costs, lack of regulation of contractual figures such as temporary contracts can lead to strong labor market segmentation and significantly increase the economic risk faced by specific population groups. In the presence of strong labor market dualization, higher redistributive needs of outsiders and those in more precarious working positions might not translate into welfare state expansions due to their lack of resources to mobilize (Rovny and Rovny, 2017).

In Chapter 2 *"Labor Market Insecurity and Preferences for Redistribution"* we study the effect of holding a temporary contract, and therefore to be exposed to stronger economic uncertainty, on individual preferences for income redistribution.[1] We obtain information on individual characteristics, redistribution preferences, and type of working contract from the European Social Survey from 2002 to 2018. As labor contracts are not randomly distributed and temporary workers tend to have different characteristics than workers with more stable positions, we use an exact matching methodology that allows us to isolate the effect of the contract type from other individual characteristics.

The results presented in the second chapter demonstrate that the degree of labor market protection induced by the contract type significantly affects individual preferences for government intervention in reducing income inequality. More specifically, we show that being subject to a temporary contract increases the probability of strongly supporting redistribution by 11 percent. Although temporary contracts affect redistribution preferences regardless of workers' gender or education level, our analysis shows that the results are mainly driven by individuals aged 40 and above. The concentration of the effect for older individuals suggests that temporary contracts create economic uncertainty when not used as a stepping stone in the job market. We extend on the role of labor uncertainty by analyzing heterogeneous effects depending on the macroeconomic context. Our results show that when risk spreads across worker groups, the differential effect of the contract type dissipates due to an increase in redistribution preferences of individuals with ex-ante more secure labor market positions.

Chapter 2 makes several contributions to the literature. First, it provides direct evidence that, beyond individual characteristics such as the level of education, gender, income, or age, holding a temporary contract increases the probability of strongly supporting government intervention to reduce differences in income levels. Second, it shows that in a context of strong dualization, expansions of labor market risk beyond the contract type imply an increase in the homogeneity of the risk pool and a reduction in the social distance between worker groups leading to a generalized increase in aggregate redistribution demand. Last, our results indicate that the risk perception associated with temporary contracts increases when they fail to convert

[1] This research is co-authored with Pilar Sorribas-Navarro.

into stable positions and are perceived as a dead-end. Our results further support the social-insurance approach to redistribution demand and contribute to the debate as to why social consensus to design policies aimed at mitigating economic inequality does not respond to increasing social polarization.

Chapter 3 approaches redistribution from a tax-design perspective. Tax and transfer instruments are among the most important tools to counteract increasing concentrations of income and wealth. Besides generating government revenue, tax instruments have the potential to reduce inequality if implemented following a progressive design. Yet, the design and implementation of tax instruments entail important behavioral responses that have substantial implications for the incidence of tax. For this purpose, the Personal Income Tax is especially relevant. In addition to being one of the main sources of government revenue,[2] personal income taxation is the instrument introducing the largest level of progressivity to the system.

The cost-efficiency trade-offs associated with the tax design become especially relevant in the presence of differences in income distribution across sub-national jurisdictions. On the one hand, marginal tax rates should be different depending on distributions of ability and the optimal extent of redistribution should rise with wage inequality (Mirrlees, 1971). Thus, the decentralization of the tax design allows regions to adapt the system based on their redistribution preferences and financial needs (Milligan and Smart, 2019; Oates, 1972). On the other hand, in a context in which individuals are mobile, centralizing the tax design prevents efficiency costs derived from behavioral responses in the form of mobility across regions (Musgrave, 1959).

Chapter 3, *"Decentralized Redistribution: The Impact of Tax Autonomy on Inequality"* focuses on the analysis of sub-national income taxation.[3] While much of previous work on tax decentralization has focused on efficiency considerations, the extent to which sub-national income taxation can reduce inequality is less documented. This chapter studies whether the decentralization of the Spanish Personal Income Tax (PIT) in 2010 affected the reduction of regional inequality achieved by the tax. We complement our analysis by documenting the effect of the pre-tax income distribution in determining the redistributive impact of the tax design and by analyzing output effects from tax policies.

To study whether the use of regions' normative power modified the redistributive effect of their tax design, we construct a micro-simulation tool that replicates the Spanish PIT design for each region and year between 2008 and 2018. We then apply this tax calculator to administrative tax records at the individual level to simulate

[2]According to the Spanish tax agency, the revenue generated from the personal income tax in 2018 accounted for 34 percent of the total tax revenue generated in the country.

[3]This research is co-authored with Dirk Foremny and Pilar Sorribas-Navarro

the redistributive impact of a given tax design when applied to different pre-tax income distributions. These simulated scenarios allow us to identify changes in regional inequality due to deviations from the central-level design. To document the effect of the pre-tax income distribution in determining the tax design's redistributive impact, we simulate counterfactual scenarios in which a given tax design is applied to different pre-tax distributions. This simulation tool further allows us to analyze output effects of tax policies. We use the identification approach of Zidar (2019) and exploit exogenous variation in central-level tax shocks due to regional differences in pre-tax income distributions.

The third chapter contributes to different strands of the literature. First, it provides descriptive evidence of the large heterogeneity in income distributions across Spanish regions. Second, it shows that granting normative power to heterogeneous sub-national regions leads to changes in regional inequality. The results indicate that the use of the region's normative power has led to an additional average reduction in the regional Gini index of 0.04 percentage points. This inequality reduction is driven by an average increase of the bottom 50 percent income share at expenses of the share of income concentrated at the top 10 percent. Last, our results parallel those of Zidar (2019) except for the average wage. We find that the average wage responds to tax changes on the top 10 percent of the income distribution, implying important incidence effects of tax hikes on this part of the population.

Chapter 4 approaches inequality and redistribution from a perspective centered around the costs and benefits of the green energy transition. To decarbonize the energy sector, the development of renewable energies imposes an important regional challenge. The development of this type of infrastructure, often located in rural areas, has been frequently presented as an opportunity to create economic activity and employment in those regions. Yet, the realization of these benefits for host communities is not automatic, and new infrastructure initiatives often encounter opposition and conflict with local residents resulting in a misallocation of investment and higher deployment costs (Jarvis et al., 2021).

From the available renewable technologies, the challenge from the development of wind energy is especially relevant. While wind is one of the most environmentally friendly sources of clean energy generation, the characteristics of this infrastructure can create significant visual and noise impacts. Furthermore, the displacement of potential alternative land uses and the perception of wind as a common good contribute to the demand from local communities for compensation (Ejdemo and Söderholm, 2015). The perception of inequality and fairness in the distribution of benefits from wind energy projects are found to prompt local opposition to the installation of wind farms (Clausen and Rudolph, 2020; Wolsink, 2007). Although the energy generated by wind power is distributed to consumption centers through the energy grid, the land and wind potential needed for this infrastructure imply its development is likely to be concentrated in some rural areas. Thus, the negative externalities associated with this type of infrastructure are geographically concentrated and put at the center of the debate the need to design compensation mechanisms to ensure a cost-efficient and socially fair energy transition.

Chapter 4 *"Blowing in the Wind: Revenue Windfalls and Local Responses from Wind Farm Development"* studies the local impact of large renewable energy projects on municipal finances and local tax responses. In this chapter, I use difference-in-differences and event-study methodologies which exploit spatial and temporal variations in the development of wind energy production installations to provide a clear causal identification of their local effects. To do so, I link data from 1994 to 2020 for local budgets to data from the Spanish Register of Energy Producers on the timing, location, and capacity of the universe of wind power plants in Spain.

The results of this chapter show that the development of a wind farm leads to a 30 percent increase in municipal revenue per capita. This effect, which first appears during the construction phase of the infrastructure, is driven by different channels. During the construction phase, municipalities benefit from wind farm development through an increase in revenue generated from indirect taxes. Once the wind farm is constructed, the effect on municipal revenue is driven by an increase in the revenue generated from direct taxes. The revenue windfalls generated by this type of infrastructure, which are partially driven by increases in the tax base, are complemented by local tax responses as municipalities use their normative capacity to maximize the revenue generated from this type of energy installation.

Chapter 4 contributes to different strands of the literature. First, it documents that wind farm development increases the local tax base and local revenue. While most of the research has focused on the U.S. setting, this is the first study analyzing a European country without specific compensation mechanisms to host communities. Second, it contributes to the literature exploring reactions to large capital-intensive projects through local tax responses. By analyzing the different categories of the property tax, I show that local tax responses take place through increases in the tax rates directly targeting capital-intensive projects and alleviating the fiscal pressure associated with other property categories. Last, it contributes to the strand of literature analyzing natural-resource windfalls. While most of the research has focused on shale oil and gas booms, I analyze the effect of wind exploitation, a natural resource with substantially different effects in terms of local employment as well as in project durability.

Finally, Chapter 5 provides closing remarks. This last chapter summarizes the main results drawn from this dissertation, discusses policy implications, and points to avenues for future research.

2. Labor Market Insecurity and Preferences for Redistribution

2.1. Introduction

Income inequality is one of the main challenges of modern societies. While free market forces tend to increase disparities within societies, market regulation and redistributive policies have the potential to mitigate economic inequality and polarization. Institutions can also play a role in mitigating income inequality. Labor market policies can have direct implications for widening or reducing income distances between population groups. Policies introducing labor market flexibility aim to promote employment creation by reducing employer costs. However, the design of these policies can lead to strong labor market segmentation and significantly increase the wage differences and the economic insecurity faced by specific population groups (Bentolila et al., 2020; Dolado, 2017; Schwander, 2019).

The redistributive function of the public sector can be perceived both as a mechanism to counteract income inequality as well as public insurance against potential income loss (Anderson and Pontusson, 2007; Cusack et al., 2006; Rehm et al., 2012). When perceived as a social insurance, demand for redistribution is predicted to be stronger not only from those with lower income (Meltzer and Richard, 1981) but also from those facing higher economic insecurity. In dual labor markets, individuals with temporary contracts have lower earnings and a higher probability of unemployment (García-Pérez et al., 2018) than individuals with permanent contracts. If temporary contracts are not perceived as a stepping stone in the job market, they can increase the perception of economic insecurity.

In this paper, we study the effect of holding a temporary contract on individual preferences for income redistribution. We focus on Spain, the European country with the largest share of labor market segmentation and large differences in employment protection depending on the employment contract. We use data from the European Social Survey for the period 2002-2018. Given that the type of contract is not randomly assigned, we apply an exact matching methodology to isolate the effect of the contract type from other individual characteristics in determining individual preferences for income redistribution.

The Spanish case, with a third of workers subject to temporary contracts, offers an ideal setting to perform this study. The structure of its labor market is highly dual, and workers face very different degrees of labor security depending on their contract type. While temporary workers, known as outsiders, are subject to low employment protection and high unemployment risk, permanent workers, known as insiders, enjoy much more protected and stable positions.[1] In this scenario, the structure of labor market institutions imply a discontinuous distribution of economic uncertainty (Rueda, 2007).

The effect of temporary contracts on the demand for redistribution can be different depending on whether individuals' current employment status is evaluated disregarding expectations to improve in the future (Marx and Picot, 2020) or if temporary contracts are perceived as a stepping stone into the labor market at young ages but as dead ends in later stages of life.[2] The macroeconomic situation can also affect the differential effect of the contract type on redistribution preferences. In periods of economic crisis, the perceived economic insecurity in the labor market can extend beyond the contract type and affect the whole population.

Our results show that holding a temporary contract increases the probability of strongly supporting government intervention to reduce differences in income levels by 4.05 percentage points. In other words, other things equal, having a temporary contract increases the probability of having a strong demand for redistribution by 11.9%. This result provides evidence supporting the perception of redistribution as social insurance. To better understand the channels through which this effect operates, we perform several heterogeneous analyses based on individuals' gender, age, and education level. Our results show that the effect of temporary contracts on redistribution preferences does not depend on individuals' gender or education level. However, it is mainly driven by individuals aged over 40, suggesting that temporary contracts create economic uncertainty when not used as a stepping stone in the job market.

We further expand on the role of economic uncertainty by analyzing heterogeneous

[1] Our status-based definition of insider-outsider is similar to the one proposed by Rueda (2007). Marx and Picot (2020) point to the possibility of the labor market status concealing heterogeneity in individual characteristics affecting redistribution preferences as an important caveat of this approach. We address this potential concern by matching individuals based on those characteristics affecting both the probability of holding a temporary contract and redistribution preferences.

[2] Empirical evidence favoring the stepping stone assumption is geographically segmented depending on the labor market characteristics. In dual labor markets such as Spain or Italy, with significant gaps in employment protection and a high incidence of temporary contracts, empirical evidence is against the stepping-stone assumption. See for example Berton and Garibaldi (2012), Gagliarducci (2005), García-Pérez and Muñoz-Bullón (2011), and Güell and Petrongolo (2007) or García-Pérez et al. (2018).

effects based on the macroeconomic context. Our results show that, although in periods of economic stability the fact of holding a temporary contract leads to higher redistribution preferences, during periods of crisis this difference disappears. When risk spreads beyond the contract type, individuals with ex-ante more secure labor market positions exhibit an increase in redistribution preferences close to levels of workers with temporary contracts.

An extensive literature has studied the determinants of the redistribution demand, both at the individual and macroeconomic levels. Individual characteristics such as the level of education, income, age, gender, or the fact of belonging to a minority group are found to be important individual determinants in shaping redistribution preferences (e.g. Iversen and Soskice, 2001; Ravallion and Lokshin, 2000; or Finseraas, 2009). Individuals beliefs (Alesina and Glaeser, 2004; Rehm, 2009), inter-generational mobility, racial and ethnic heterogeneity (Alesina and Glaeser, 2004; Lupu and Pontusson, 2011), and (perceived) inequality (Alesina et al., 2018) are also important determinants of redistribution demand. Our study focuses on the role of perceived economic insecurity due to the labor market institution.

We make three contributions to the existing literature. The strand of political economy literature studying the relationship between labor market risk and preferences for redistribution has focused on individuals' exposure to risk varying within education, occupation, and industries to explain the demand for social spending (see for example Cusack et al., 2006; Iversen and Soskice, 2001; Moene and Wallerstein, 2001; Rehm, 2009, 2011; or Ravallion and Lokshin, 2000). We contribute to this body of literature by showing that, additionally to the effect of individuals' education level or occupation sector, the contract type directly affects individuals' redistribution preferences.

Most of the existing literature studying the intersection of insider-outsider divides and social policy attitudes provide evidence of stronger redistribution preferences and social insurance demand of temporary workers (Burgoon and Dekker, 2010; Häusermann et al., 2015, 2016; Marx, 2014; Marx and Picot, 2013) are studies focusing on multi-country cross-section methodologies and provide insight on general trends. With our analysis, we contribute by providing causal evidence of the effect of the contract type on redistribution preferences. Finally, our heterogeneous analysis provides some evidence about the mechanisms causing the differential effect of the contract type on redistribution preferences.

Our results contribute to explaining the observed puzzle of the limited response of the public sector to satisfy the redistribution demand of some population groups. The median voter model predicts that higher inequality should lead to an increase in redistribution demand taken into consideration by policymakers. In dual labor markets, where the division of contracts extends workers' heterogeneity beyond their skill set, the lack of responsiveness can be explained by the lower perception of risk of those in more secure labor market segments (Alt and Iversen, 2017).[3] Furthermore, outsiders tend to be less organized and lack the resources to mobilize (Rovny and Rovny, 2017), and political goals are often best served by pursuing policies that benefit insiders while ignoring the interests of outsiders (Rueda, 2005). From a policy-making perspective, our results contribute to the already existing broad literature that has documented the negative effects of temporary contracts, such as lower wages or mental and physical health levels.[4] All these empirical evidences highlight the need to reform the labor market to mitigate the negative effects caused by temporary contracts.

The rest of the paper is structured as follows. Section 2 explains the institutional setting, describing the characteristics of the Spanish Labor Market and the macroeconomic situation of the period of analysis. Section 3 presents the data, documenting how the preferences for redistribution are measured and the distribution of labor contracts by some individual characteristics. Section 4 explains the empirical strategy. Section 5 presents the baseline results, the heterogeneous analysis, and robustness checks. Section 6 concludes.

2.2. Institutional Setting

2.2.1. The Spanish Labor Market

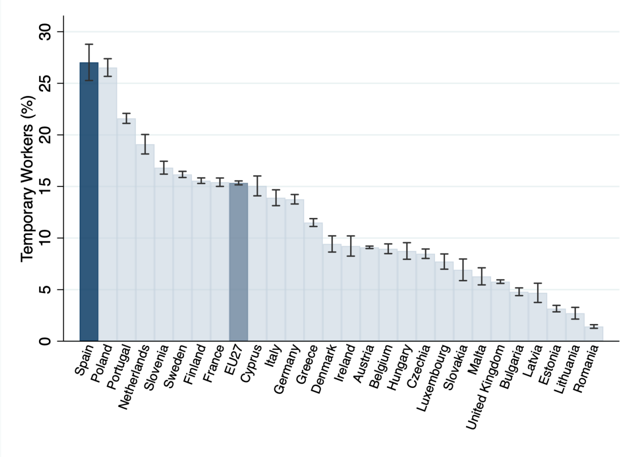
Spain's labor market, with significant differences in labor regulations applied to workers, is characterized by its duality. Workers with permanent contracts, known as insiders, are subject to stricter regulations and enjoy higher job security. Workers with temporary contracts, known as outsiders, are subject to a more lenient regulation and have lower job security. Although temporary workers are present in all European labor markets, Spain is the country with the largest degree of duality. As Figure 2.1 shows, from 2005 to 2019, on average 27 percent of Spanish workers held temporary contracts. This percentage is significantly higher than the average of the European Union (15.3 percent) and all other EU countries except Poland.

The duality of the Spanish labor market was precipitated by the 1984 labor market

[3] Alt and Iversen (2017) develop a model which combines altruism and heterogeneity with self-interest and insurance motives to show that labor market segmentation affects redistribution demand. They use survey data from the International Social Survey Program from 1985 to 2001 to provide evidence supporting the insurance theory with a segmented labor market model. Their results show that dual labor markets are related to lower levels of redistribution support than non-segmented labor markets.

[4] See for example Bartoll et al. (2018), Bentolila et al. (2008), Booth et al. (2002), Dolado et al. (2002), Green (2020), and Guadalupe (2003), or Michaud et al. (2016).

Figure 2.1.: Share of Temporary Workers, EU-27



Notes: Average share of temporary workers in each European country from 2005 to 2019 and corresponding standard errors. Data from EUROSTAT.

reform, which liberalized the use of temporary contracts. Prior to this reform, open-ended contracts were the norm, and temporary contracts were reserved for inherently temporary jobs. In response to the high increase in unemployment during the first half of the 1980s and the need to modernize the Spanish labor market, the 1984 reform removed the temporary nature requirement of fixed-term contracts allowing its use for any job.

In practice, the liberalization of the use of temporary contracts derived in the segmentation of the labor market between unstable low-paid and stable highly-payed jobs. During the late 1980s, more than 90 percent of new contracts created were temporary, and the conversion rate of temporary to permanent contracts was below 10 percent. These two facts implied little creation of permanent employment (Güell and Petrongolo, 2007). With two-thirds of employees retaining a permanent status and the rest working in a highly mobile market, the extensive use of temporary contracts implied a large gap in employment protection between workers with different contract types.[5] The use of temporary contracts is not homogeneously distributed across the population and has a high incidence amongst some population groups such as

[5]The regulation on employment protection was very different for both contract types. According to Law 32/1984, temporary contracts could have a duration between six months and three years with severance payments of 12 days per year of service. For permanent workers, dismissal payments were 45 days per year of job tenure with a maximum of 42 months of wages. The role of labor unions further worsens the situation of temporary workers. Even though labor unionism in Spain is relatively low, over 80% of workers are affected by union negotiations. As mainly those with stable employment tend to participate in workers' council elections, such agreements tend to focus on permanent workers' needs and widen the gap in labor protection between insiders and outsiders (Amuedo-Dorantes, 2000; Rueda, 2007).

younger individuals, women, and those with lower education levels.

Since 1994, several reforms have attempted to mitigate the dualism of the labor market by reducing the dismissal costs associated with open-ended contracts. Yet, their effects have been limited. By the mid-2000s, the number of temporary contracts, with a conversion rate of 6 percent, was more than 20 times the flow of net employment growth (Bentolila et al., 2012). In 2022 a new labor market reform was implemented in Spain to increase labor stability.[6]

Spain provides an ideal setting to study whether the existing design of the dual market generates (perceived) economic insecurity and increases the demand to mitigate income inequality. For an outstanding share of individuals, labor income is the main source of income. In our period of analysis, the Spanish labor market remains strongly dual, with two clearly identified segments of the population facing very different labor market protection. This exercise tests if the redistribution function of the public sector is perceived as social insurance.

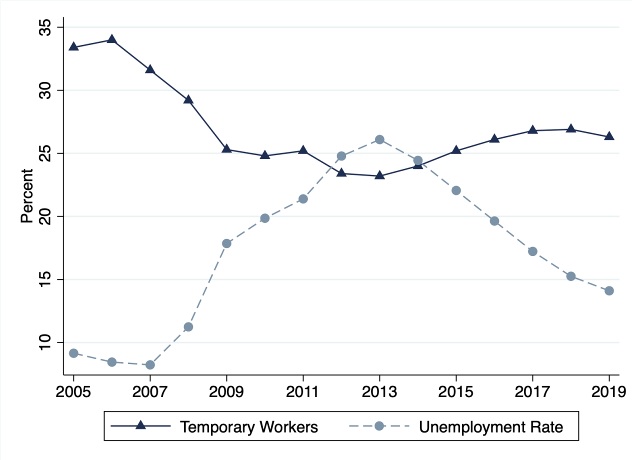
2.2.2. Macroeconomic Environment

The period analyzed, 2002-2018, encompasses two very different economic contexts marked by the Great Recession. The period from 2002 to 2007 is characterized by a low unemployment rate and a strong housing boom fueled by easy credit accessibility. In 2007, when the economic crisis started to show its first signs in the United States, the Spanish economy was accumulating a 14-year period of continuous growth and an unemployment rate of 8 percent. As shown in Figure 2.2, in Spain, the Great Recession started to significantly affect the economy by 2009, when unemployment rates surged, property prices started to drop, and internal demand contracted. The severity of economic uncertainty was further worsened by the 2012 sovereign debt crisis, which resulted from the high levels of public debt accumulation and implied the implementation of extensive structural reforms and austerity measures. It was not until 2014 that Spain exhibited indications of initial economic recovery, with gradual improvements in GDP growth and a decline in unemployment rates.

The onset of the Great Recession and the subsequent increase in unemployment rates propagated economic uncertainty across worker groups. Figure 2.2 documents the evolution of the unemployment rate and the share of temporary workers in the Spanish economy between 2005 and 2019. In the initial stages of the crisis, the lack of adequacy of labor conditions and lower dismissal costs of temporary employees

[6] The period included in our analysis does not include this last reform. So far, the data available seems to provide evidence that this reform, which establishes more limits on the use of temporary contracts, has reduced the use of this type of contract.

Figure 2.2.: Evolution of unemployment rate and share of temporary workers, Spain



Notes: Evolution of unemployment rate (circles) and percentage of temporary workers (triangles) in Spain for years from 2005 to 2019. Data from EUROSTAT.

implied that the labor market adjustment mainly occurred through the dismissal of temporary workers. The reduction in temporary employees, which disproportionately affected young people and the lesser qualified, accounted for more than 60 percent of the total employee reduction (Ortega and Peñalosa, 2013).

The 2010 and 2012 employment laws further promoted the use of employment regulation measures implemented during the crisis. To reduce the public deficit and promote long-term employment, the 2010 and 2012 employment protection laws increased the flexibility of the labor market by decreasing dismissal costs and relaxing dismissal opportunities.[7] The 2010 employment law facilitated individual dismissal by recognizing company losses as a legitimate reason for worker dismissal and reducing the number of severance payment days from 45 to 33. The 2012 employment also included more extensive and regulated aspects, such as the decentralization of the collective bargaining process, which diminished the power of labor unions. This new employment law further expanded the causes of collective dismissal by introducing economic reasons for worker dismissal, eliminated the need for previous administrative authorization, and reduced the period of compensation entitlement to employees from 42 to 24 months.

[7]These reforms facilitated the use of "Employment Regulation Procedure" and "Temporary Employment Regulation Procedures", which refer to a legal procedure that companies use to manage workforce adjustments due to economic, technical, organizational, or production-related reasons. While "Employment Regulation Procedures" imply the termination of the contract, "Temporary Employment Regulation Procedures" refers to a temporary employment suspension or a reduction of working hours with employees often receiving unemployment benefits during the suspension period. In the Appendix, Figure A.1 documents the evolution of workers affected by each type of procedure over our period of analysis.

Although it was in 2011 when permanent employment fell for the first time below the 2007 level (Bentolila et al., 2012), the use of employment regulation procedures mainly targeted workers with more protected positions in the labor market. Workers affected by this type of regulation procedures, which increased from 58,000 in 2007 to 483,000 in 2012, where predominantly men, individuals with university education, and workers with job tenure (Izquierdo et al., 2021).

The dismissal of temporary workers and the extensive use of employment regulation measures implied an expansion of labor risk across all segments of the population. Beyond the employment protection offered by their contract type, all workers faced a higher probability of losing their jobs and increases in the average time of unemployment. The percentage of unemployment with duration of over one year went from 21 percent before the crisis to 58 percent in 2013. Unemployment duration became especially long for individuals with low levels of education as well as for the youngest and oldest workers, bringing them into a situation of risk of exclusion from the labor market (Ortega and Peñalosa, 2013).

The macroeconomic context and the reaction of the labor market provide evidence supporting the prediction that, in times of economic crisis, the perception of economic insecurity can increase for workers with permanent contracts. Thus, in our analysis, we estimate whether the effect of contract type on the preferences for redistribution differs depending on the macroeconomic context. This additional analysis further expands the study of the role of economic insecurity on redistribution demand.

2.3. Data

Our analysis is based on data from the European Social Survey (ESS). In addition to socio-demographic characteristics, this survey collects information about individuals' preferences for redistribution and their type of employment contract. In the Spanish context of a dual labor market with low conversion rates to permanent contracts, we proxy economic uncertainty by the type of contract the individual holds. We use data for Spain from the nine survey rounds conducted before the COVID-19 crisis, 2002-2018.[8]

[8]The European Social Survey is a biennial cross-national survey collecting information about the preferences and behavior of a representative sample of individuals aged 15 and above. To randomize the sample selection, strata are constructed by combining the region of residence and the size of the habitat. The years of the surveys are the following: 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, and 2018.

2.3.1. Sample

Our sample consists of individuals active in the labor market aged 70 or below. More specifically, we restrict our sample to individuals reporting a paid job as a main activity or who had done some paid work within the last seven days. To ensure that our analysis does not include retired individuals who may disproportionately benefit from welfare state expansions, we exclude individuals who report being retired or are aged above 70, even if they report some recent paid work.[9] To compare individuals with similar exposure to economic uncertainty due to their situation in the labor market, we exclude from our analysis individuals who, although active in the labor market, report to be self-employed or working in a family business. Our initial sample is composed of 7,727 individual observations.[10]

2.3.2. Preferences for Redistribution

Our dependent variable measures preferences for income redistribution through answers to the following question, in which interviewees could select one of the five alternatives:[11]

"Please say to what extent you agree or disagree with the following statements: The government should take measures to reduce differences in income levels."

(1) *"Disagree Strongly"*

(2) *"Disagree"*

(3) *"Neither Agree nor Disagree"*

(4) *"Agree"*

(5) *"Strongly Agree"*

[9]By including individuals who report having done paid work during the last seven days, we also capture individuals whose current main occupation may be different than paid work. In a robustness check, we provide evidence that these individuals do not drive our results (see Appendix C.3).

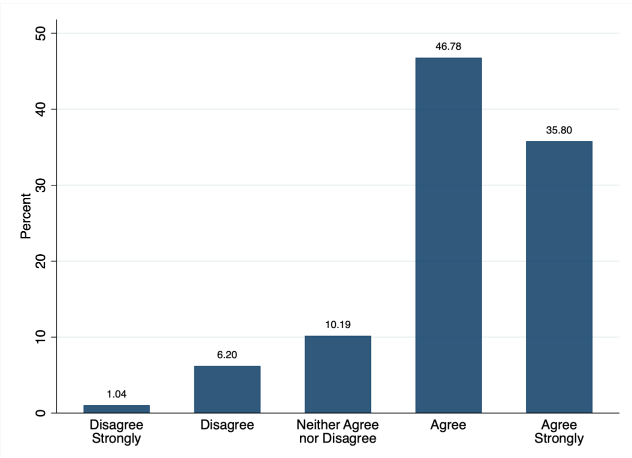
[10]The original database is composed of 17,169 observations. From those, 16,634 individuals provide information on redistribution preferences. Among them, 13,309 are non-retired individuals aged 70 or below. The sample is further reduced to 9,449 observations after restricting it to individuals active in the labor market and excluding those who are self-employed or working in a family business, and to 7,727 observations when considering individuals who provide information on the contract type, the characteristics used in the matching process and about their political ideology.

[11]The original question is coded as: (1) Agree Strongly, (2) Agree, (3) Neither Agree nor Disagree, (4) Disagree, and (5) Disagree Strongly. To facilitate the interpretation of the results, we recode the answer giving the highest value (5) to the strongest (agree strongly), and a value of (1) corresponds to the lowest preferences for income redistribution. Responses coded as (7) Refusal, (8) Don't know, and (9) No answer, are treated as missing values.

This question has been used in multiple studies to capture individuals' preferences for redistribution.[12] The answers to this question capture the preferences for government redistribution, which can be considered as a form of social insurance against potential income shocks that individuals may face.

Figure 2.3 shows the distribution of responses across the various alternatives. Over 80 percent of the responses are concentrated on categories 4 "Agree" and 5 "Strongly Agree". This pattern is consistent across all survey waves and is not due to the definition of our sample.[13] The concentration of the largest share of respondents in these two categories, which indicates strong support for government intervention to reduce income inequality, may be attributed to a desirability bias. However, this bias is not expected to significantly affect the allocation of respondents between these two options. Hence, the main focus of our analysis will be on the variation in the intensity of support for redistribution. We define individuals with a strong demand for redistribution as those who strongly agree with the statement that government should take measures to reduce income inequalities.

Figure 2.3.: Distribution of Preferences for Redistribution



Notes: Percent of respondents for each category of preferences for income redistribution. Data correspond to our final sample of respondents to the European Social Survey for the waves from 2002 to 2018 before implementing the matching. This sample consists of working individuals aged 70 or below active in the labor market who answered all the questions used in the analysis.

[12]Studies such as Dimick et al. (2018), Fernández-Albertos and Manzano (2016), Finseraas (2009, 2012), and Rehm (2009) have employed this question. For a similar question from the International Social Survey Program (ISSP), see Alt and Iversen (2017), Cusack et al. (2006), or Corneo and Grüner (2002).

[13]In Appendix A, Figure A.2 shows that the selected sample does not condition the distribution of preferences. The share of individuals allocated to each category is the same when we consider a) all the individuals that have answered this question, b) when we restrict the sample to those that are active in the labor market, aged 70 or below, and not reporting to be retired, and c) when we additionally restrict the sample to individuals for whom we have information on all the questions needed in our analysis.

2.3.3. Type of Employment Contract

We obtain information on individuals' labor contract from answers to the following question:[14]

"Do/did you have a work contract... "

(0) *"Permanent"*

(1) *"Temporary"*

The dualism of the Spanish labor market implies that 33.7% of our sample's observations are individuals with a temporary contract, characterized by being subject to much laxer regulation and higher levels of job insecurity. However, an individual's contract type is not randomly determined. The literature has broadly documented that the probability of having a temporary contract correlates with the following observable characteristics: education, age, gender, having been on long-term unemployment,[15] and belonging to a minority group.

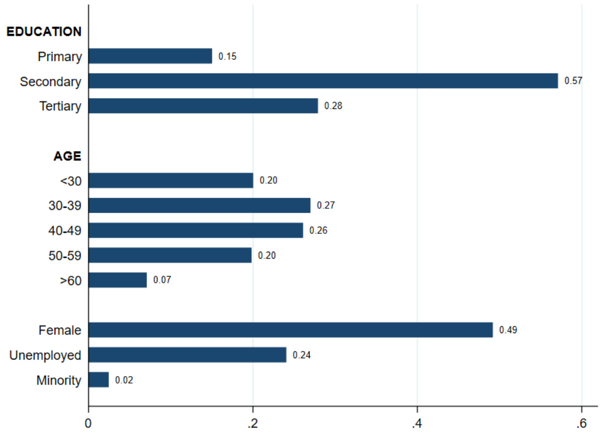
Figure 2.4 shows the distribution of the characteristics affecting the probability of having a temporary contract in our sample. Panel (a) includes all observations in our final sample. Panels (b) and (c) show the distributions for permanent and temporary workers, respectively. As Panel (c) in Figure 2.4 documents that among individuals with a temporary contract, 18% have completed primary studies, 62% have completed secondary studies, and 21% have completed tertiary studies. In terms of age, the concentration of temporary workers substantially decreases as we advance in age brackets. Among temporary workers, 36% are less than 30 years old, and 27% fall between 30 to 40 years old. In terms of gender, 55% of individuals with a temporary contract are women. Finally, 36% of temporary workers have been on long-term unemployment, and 4% identify as belonging to a minority group.

[14]The original question is coded as: (1) "Unlimited", (2) "Limited". To facilitate the interpretation of the analysis, we recode the variable as follows: (1) "Temporary" which corresponds to "Limited", and (0) "Permanent" which corresponds to "Unlimited". Options (3) "No contract", (6) "Not applicable", (7) "Refusal", (8) "Don't know", and (9) "No Answer", are treated as missing observations.

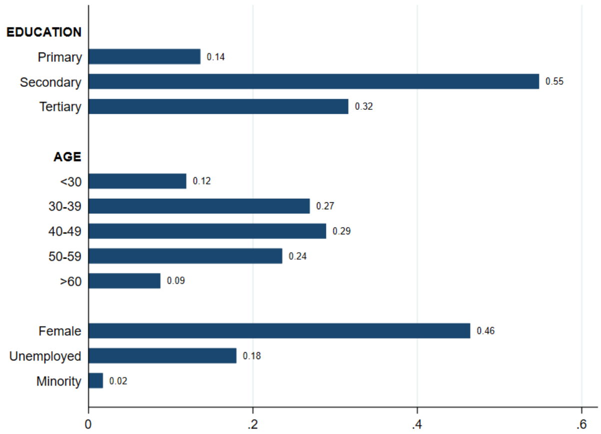
[15]We identify previous unemployment from answers to the question "Have you had any period of unemployment and work seeking that lasted 12 months or more?"

Figure 2.4.: Distribution of Personal Characteristics by Type of Contract

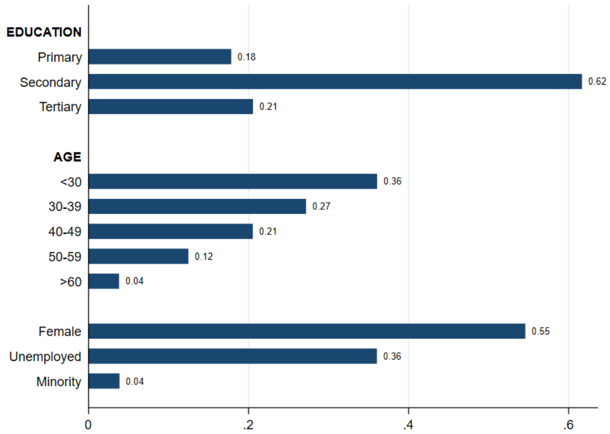
(a) Full Sample



(b) Permanent Contract

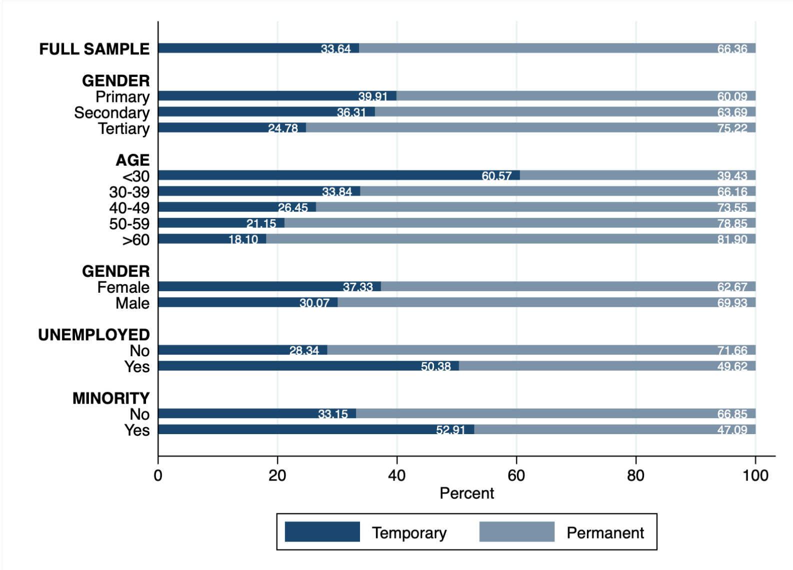


(c) Temporary Contract



Notes: Sample of respondents to the European Social Survey for the years 2002 to 2018 before matching. Data corresponds to our final sample which includes working individuals aged 70 or below with information on all the variables used in the analysis.

Figure 2.5.: Distribution of Contracts Based on Individual Characteristics



Notes: Sample of respondents to the European Social Survey for the years 2002 to 2018 before matching. Data corresponds to our final sample which includes working individuals aged 70 or below with information on all the variables used in the analysis.

The characteristics of temporary workers substantially differ from the whole sample (Panel a) and permanent workers (Panel b). On average, temporary workers have lower levels of education, are younger, and have a higher proportion of women, individuals who have experienced long-term unemployment, and individuals who belong to a minority group. In contrast, individuals with permanent contracts exhibit an inverse pattern. In Figure 2.4, Panel (b) shows that, compared to the overall population, individuals with a permanent contract have, on average, higher levels of education, are older, and are less likely to be a woman, an individual who has experienced long-term unemployment, or an individual belonging to a minority group.

Figure 2.5 provides additional descriptive evidence corroborating that the type of labor contract is not randomly assigned. This figure documents the incidence of temporary contracts for the full sample and within the different population groups. Although in the whole sample 33.6% of the individuals have a temporary contract, the incidence of this contract type varies substantially depending on characteristics such as the level of education, age, and gender. Among individuals with tertiary education, only 24.7% have a temporary contract. The share of temporary workers increases to 36.3% for those with secondary education, and to 39.9% for those with primary education.

The incidence of temporary contracts is particularly relevant for young individuals and decreases as age increases. This is consistent with temporary contracts acting as a stepping stone in the labor market. Among individuals under the age of 30, 60.6% have a temporary contract. This share goes down to 33.8% for individuals aged between 30 and 40, and decreases to a non-negligible 18% for individuals aged 60 and above. Regarding gender, temporary employment is more prevalent among women than men. While 30% of men hold a temporary contract, this figure increases to 37% for women. Finally, the incidence of temporary contracts for individuals who have not experienced long-term unemployment and those who do not belong to a minority group is close to the incidence for the full population, around 30%. Yet, 50% of the individuals who have previously been long-term unemployed and 53% of the individuals who belong to a minority group are subject to a temporary contract.

2.4. Empirical Strategy

The aim of this paper is to identify the effect of perceived economic uncertainty on individual preferences for income redistribution. As discussed above, we proxy economic uncertainty by having a temporary labor contract. In a scenario where labor contracts were randomly assigned unconditionally on workers' characteristics, the effect of the contract type on the preferences for redistribution could be identified by estimating the following equation:

$$PrefRedist_{i,R,t} = \alpha + \beta_1 Temporary_{i,R,t} + \varepsilon_{i,R,t} \tag{2.1}$$

where $PrefRedist_{i,R,t}$ is the preference for redistribution of individual i in region R, in year t. $Temporary$, is the main explanatory variable and equals to one if individual i holds a temporary contract and zero if the contract is permanent. The residual, ε, is assumed to be identical and independently distributed.

Equation (2.1) compares the preferences for redistribution of two groups of individuals, those with a temporary contract and those with a permanent contract. To establish a causal interpretation of the effect of a temporary contract, these two groups should be identical in every possible dimension that affects preferences for redistribution, except for the type of contract. Thus, the main challenge in this analysis is that the assignment of contract type to individuals is not random. As documented in the previous section, the probability of having a temporary contract is higher for individuals with lower levels of education, younger individuals, females, and individuals who have experienced long-term unemployment or belong to a minority group. Moreover, these characteristics correlating with the type of employment contract have also been identified in the literature as determinants of redistribution preferences.

We employ an exact matching procedure to address the non-random assignment of temporary contracts. This procedure enables us to create a sample of individuals with a different type of contract but that are equal in those observable characteristics determining both the fact of holding a temporary contract and the preferences for redistribution. Thus, after implementing the exact matching, we can consider the contract assignment to be as good as random. This matched sample allows us to identify the causal effect of temporary contracts on preferences for redistribution.

2.4.1. Matching

The empirical strategy we employ is based on a selection on observables. To isolate the effect of the contract type, we apply an exact matching methodology. This approach enables us to control for the potential confounding variables and estimate the average treatment effect on the treated (ATT) without relying on specific modeling assumptions (Iacus et al., 2012).[16] To satisfy the non-omitted variable bias assumption, the treatment variable (holding a temporary contract) must be independent of the potential outcomes conditional on covariates. By using the covariates determining the treatment in the matching procedure, which in this case is the fact of holding a temporary contract, the treatment assignment becomes a random fact, and we are able to estimate its causal effect.

Thus, the variables incorporated in the matching must capture the characteristics correlated with the fact of holding a temporary contract and must be considered also determinants of individuals' preferences for redistribution. We select those variables based on the findings and evidence provided by the existing literature. Previous studies looking at the characteristics of temporary workers in Spain indicate that this contractual figure has a higher incidence amongst younger individuals, women, and those with lower education levels. Furthermore, individuals with temporary contracts are found to be more likely to belong to a minority group and to have been unemployed previously (Amuedo-Dorantes, 2000; Dolado et al., 2002; OECD, 2002; Polavieja, 2006). This is in line with the patterns described by Figure 2.4 and Figure 2.5 which document the correlation between these observable characteristics and the contract type in our sample. Besides affecting the probability of holding a temporary contract, these individual characteristics have also been identified to influence individual preferences for income redistribution (Cusack et al., 2006; Finseraas, 2012; Ravallion and Lokshin, 2000; Rehm, 2009).

More specifically, the individual-level variables used in the matching are *Education*, categorized as primary, secondary, or tertiary; *Age*, grouped into brackets of

[16] Exact matching restricts the matched data to areas of common empirical support and meets the congruence principle, which requires the data space and analysis space to be the same (Blackwell et al., 2009; Iacus et al., 2012).

less than 30, 30 to 39, 40 to 49, 50 to 59, and 60 or more; *Female*; *Unemployed*, indicating whether an individual has been unemployed and seeking for work for a period of 12 months or more; and *Minority*, indicating whether an individual belongs to a minority group.[17] In Table 2.1, Panel (a) presents the differences in means for all these observable characteristics between the group of individuals with a temporary contract and those with a permanent contract. The imbalances documented in this table corroborate the need to implement the matching procedure.

Table 2.1.: Differences in Means Between Treated and Control Groups: Variables Used in the Matching

	(a) Unmatched Sample (N=7,727)				(b) Matched Sample (N=6,984)			
	Temporary	Permanent	t-test	(p value)	Temporary	Permanent	t-test	(p value)
Education								
Primary	0.178	0.136	4.917	0.000	0.159	0.159	0.000	1.000
Secondary	0.616	0.548	5.753	0.000	0.635	0.635	0.000	1.000
Tertiary	0.205	0.316	-10.316	0.000	0.206	0.206	0.000	1.000
Age								
Less than 30	0.361	0.119	26.155	0.000	0.347	0.347	0.000	1.000
30 to 39	0.272	0.269	0.237	0.813	0.275	0.275	0.000	1.000
40 to 49	0.205	0.289	-7.970	0.000	0.211	0.211	0.000	1.000
50 to 59	0.125	0.236	-11.652	0.000	0.130	0.130	0.000	1.000
More than 60	0.038	0.087	-8.011	0.000	0.036	0.036	0.000	1.000
Female	0.546	0.464	6.771	0.000	0.548	0.548	0.000	1.000
Unemployed	0.360	0.180	17.882	0.000	0.333	0.333	0.000	1.000
Minority	0.038	0.017	5.690	0.000	0.014	0.014	0.000	1.000

Notes: Differences in means between individuals with a temporary and a permanent contract. Data corresponds to our final sample which includes working individuals aged 70 or below with information on all the variables used in the analysis. Panel (a) corresponds to the sample before matching. Panel (b) corresponds to the matched sample.

As an initial step before the matching process, we estimate a Probit model to corroborate the association of the selected variables to be used in the matching with the individual contract type. We use as a dependent variable a dummy taking a value of one if the individual has a temporary contract and zero otherwise. The explanatory variables consist of the individual characteristics discussed above deemed to affect both the contract type and redistribution preferences. The Probit model results are reported in Table B.1 of Appendix B. All coefficients are statistically significant and have the expected sign. Specifically, higher levels of education and age are associated with a lower probability of having a temporary contract, while being a female, having a history of long-term unemployment, and belonging to a minority group are associated with a higher probability. These results are robust to the inclusion of time and region-fixed effects. We include time-fixed effects to capture

[17] In Appendix A, Table A.1 documents the exact definition of these variables and their summary statistics.

the temporal differences in the economic situation and regulations that could impact the prevalence of temporary contracts. Regional fixed effects capture differences in economic structure and economic situation across regions.

We match individuals within each survey wave based on the characteristics identified as determinants of the contract type and redistribution preferences: *Education*, *Age*, *Female*, *Unemployed* and *Minority*. Given that all these variables are categorical, we implement a coarced exact matching.[18] Exact matching divides the sample into strata so that all individuals inside a strata have the same observable characteristics and only differ in the type of contract they hold. After the matching process we can estimate the causal effect of temporary contracts on preferences for redistribution as holding a specific contract is considered as random.

The underlying trade-off of this methodology results from the number of strata and bins used to match individuals. Larger bins result in fewer strata, and fewer strata result in more diverse observations and, therefore, higher imbalance (Blackwell et al., 2009). Our sample size restricts the number of variables that can be included in the matching. First, specific regional variation cannot be eliminated by implementing the matching within regions as it results in a substantial loss of observations. Yet, there are significant differences among regions in terms of redistributive policies that need to be controlled for in the estimations. A significant share of the welfare spending in Spain is decentralized at the regional level through education, health, and social protection. The structure of the economic activity and the economic situation also varies over regions. We include regional fixed effects in our estimations to capture variation within regions. Second, to isolate the effect of economic uncertainty derived exclusively from the contract type, the matching should include the income level.[19] We include in the matching the main predictors of the income level (age, education, and gender).[20] To verify that our matching specification does not affect our results, we perform several robustness tests.[21]

Our final matched sample consists of 6,984 individual observations.[22] In Table 2.1, Panel (b) shows that in our matched sample there are no statistically significant

[18]Age is the only continuous variable used in the matching procedure. To select individuals from the same age range, we recode the variable into five categories as shown in Table A.1 of Appendix A.

[19]Starting in the baseline model of redistribution demand developed by Meltzer and Richard (1981), income has been considered as a main determinant of individual demand for redistribution.

[20]We do not include income level in the matching to avoid a substantial reduction in the sample size due to the increase in the number of strata and the fact that a significant share of individuals does not answer the income question. Moreover, this question varies over survey waves.

[21]In Section 2.5.4, we show that our baseline results are robust to implementing matching within regions or including income in the matching specification. We also perform an additional robustness test where we control for the sector of economic activity where the individual works.

[22]From our original sample of 7,727 observations, we do not find a match for 743 observations, 172 of which are individuals with a temporary contract.

differences in means of observable characteristics between workers with temporary and permanent contracts. In Appendix B, Table B.2 further demonstrates that all initial differences between the group of individuals with permanent and temporary contracts along the distribution are eliminated after the matching process.[23] It is important to stress that while the matching process allows the selection of individuals with similar characteristics, it does not bias the share of temporary workers or the distribution of redistribution preferences in our sample. Before performing matching, 33,64 percent of our observations consist of temporary workers. In our matched sample, this proportion remains at 34,75 percent. In Appendix B, Figure B.1 illustrates that the distribution of preferences for redistribution is very similar in our matched and unmatched samples.

2.4.2. Estimation

When the matching procedure is exact, a simple difference in means is enough to estimate the treatment effect (Blackwell et al., 2009). However, using a parametric framework allows to choose the most appropriate estimation model. We estimate Equation (2.1) using an Ordered Logit model on our matched sample to account for the categorical nature of our dependent variable. Estimating the effect of the contract type through an ordered logistic regression further allows to control for some variables that, although potentially affecting redistribution preferences, are not included in the matching. To account for the importance of each observation, our estimators weight each observation according to the size of their strata (Blackwell et al., 2009; Iacus et al., 2012).[24] We cluster standard errors at the region level.

A positive and statistically significant β_1 coefficient indicates a positive effect of labor market uncertainty on redistribution preferences and provides evidence supporting the insurance theory. To strengthen the causal interpretation of our results, we include additional controls in our analysis. These controls include individual political ideology, region-fixed effects, time-fixed effects, their interaction, and the variables used in the matching process.

We add political ideology as a control variable to account for its potential influence on preferences for redistribution.[25] Previous research has shown a strong association

[23]In Appendix B, Table B.2 reports the multivariate L1 distance statistic and the differences within the distribution of each variable. The L1 statistics is a comprehensive measure of global imbalance and takes a value of 0 to indicate perfect balance and a value of 1 to indicate complete imbalance. In our analysis, after implementing the matching, both the multivariate L1 distance and the L1 measure for each variable are equal to 0, indicating that the distribution of the variables in treated and control groups is balanced.

[24]We apply iweights in all regressions.

[25]*Political ideology* is self-reported using a 0 (extreme left) to 10 (extreme right) scale.

of political ideology with preferences for income redistribution as supporters of right-wing parties tend to express less support for social spending than supporters of left-wing parties (Cusack et al., 2006; Fernández-Albertos and Manzano, 2016). We then include regional fixed effects to control for omitted variables at the regional level that can determine both redistribution preferences and the type of contract held. These dummies capture factors such as differences in the welfare state across regions and differences in economic structure. By adding regional fixed effects, we control for regional variation that could not be eliminated through the matching procedure. We then add time-fixed effects to control for time-related factors common over the country but varying over time. To control for region-specific time differences, we then include the interaction of the region and time-fixed effects. Finally, we include the variables used in the matching as control variables.[26] The stability of the estimated coefficients across the different specifications corroborates the causal interpretation of our results.

The coefficient obtained from Ordered Logit estimations is not directly interpretable quantitatively. Thus, we estimate the average marginal effects (AME) of holding a temporary contract for each of the five categories of the preferences for redistribution. The marginal effect is computed as the difference in the predicted probability of choosing one of the five redistribution categories as the contract type variable changes from zero (permanent contract) to one (temporary contract), while all other variables are held constant at their mean values. Intuitively, it treats an individual i as though she/he holds a permanent contract, regardless of the contract type held, and computes the probability of this individual supporting preferences for redistribution j. Then, it treats the same individual i as if she/he holds a temporary contract and computes again the probability of supporting the same level of redistribution j. The difference between both probabilities is the marginal effect of the individual i on supporting preferences j. Once this process is repeated for all the sample, the average of such marginal effects gives the AME of temporary contracts on preferences for redistribution.

After estimating the average effect of having a temporary contract on redistribution preferences, we proceed to study whether this effect is heterogeneous depending on individual characteristics and the macroeconomic situation.[27] Specifically, we examine the heterogeneity of the effect based on individuals' level of education, gender, and age. To further explore whether economic uncertainty affects redistri-

[26]Given the goodness of the matching, including these variables as controls should not affect the estimated coefficient

[27]To estimate heterogeneous effects we estimate Equation (2.1) adding an interaction of our main dependent variable, *Temporary*, with a variable capturing the individual characteristics or the macroeconomic situation.

bution preferences, we estimate the effect of the temporary contract in periods of economic crisis versus periods of no economic crisis. This heterogeneous analysis provides insights into the mechanisms determining redistribution demand in dual labor markets by examining the interplay between labor market uncertainty, individual characteristics, and the macroeconomic environment.

2.5. Results

2.5.1. Baseline Results

We start by presenting in Table 2.2 the baseline results from estimating Equation (2.1) using an Ordered Logit model on our matched sample.[28] The positive and statistically significant coefficient of *Temporary* reported in Column (1) indicates that, without including any additional control, holding a temporary contract leads to an increase in individual preferences for income redistribution. Column (2) shows that this effect is persistent when including individuals' political ideology as a control. As expected, the coefficient estimated for political ideology is negative and statistically significant, indicating lower preferences for income redistribution of right-wing individuals. These results remain quantitatively unchanged when we control for region-fixed effects (Column 3), time-fixed effects (Column 4), their interaction (Column 5), and the individual characteristics used in the matching (Column 6). The robustness of the results to the inclusion of additional controls provides additional validation for the effectiveness of our matching specification in balancing the sample in terms of the observable characteristics.

To provide information about the quantitative interpretation of the estimated Ordered Logit coefficients, Figure 2.6 represents the estimated average marginal effects (AME) and the 95% confidence interval of holding a temporary contract for each of the five categories of redistribution preferences.[29] This figure illustrates that holding a temporary contract positively affects the probability of agreeing with the highest level of redistribution while decreasing the probability of supporting any of the other levels. In Table 2.3, row (a) reports the estimated value of these AMEs. All of them are statistically significant at the 99% level. The results reported in Column (5) indicate that holding a temporary contract increases by 4.05 percentage points the probability of strongly agreeing with the statement *"The government should take measures to reduce differences in income levels"*. Conversely, holding a

[28] Results from performing a cut-point test suggest that none of the categories can be collapsed and indicate that the Order Logit model is the most appropriate estimator to implement in this analysis.

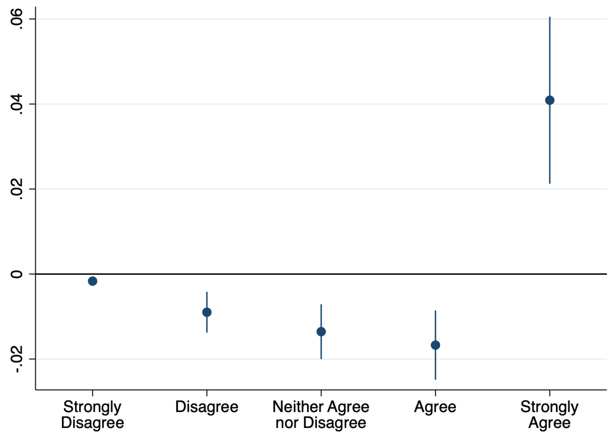
[29] The AMEs reported in Figure 2.6 correspond to the specification reported in Column (6) of Table 2.2.

Table 2.2.: Effect of Temporary Contract on Preferences for Redistribution

	(1)	(2)	(3)	(4)	(5)	(6)
Temporary	0.211***	0.178***	0.163***	0.173***	0.194***	0.192***
	(0.066)	(0.062)	(0.061)	(0.055)	(0.049)	(0.047)
Pol. Ideology		-0.144***	-0.142***	-0.138***	-0.137***	-0.137***
		(0.021)	(0.021)	(0.022)	(0.021)	(0.020)
N	6,984	6,984	6,984	6,984	6,984	6,984
RFE	NO	NO	YES	YES	NO	NO
TFE	NO	NO	NO	YES	NO	NO
RFE*TFE	NO	NO	NO	NO	YES	YES
Controls	NO	NO	NO	NO	NO	YES

Notes: Results from estimating Equation (2.1) on our matched sample. Coefficients corresponding to the estimation of an Ordered Logit model. The dependent variable, *PrefRedist*, corresponds to our measure of preferences for income redistribution. Standard errors clustered at the region level are in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 2.6.: Average Marginal Effects of Temporary Contract on Preferences for Redistribution



Notes: Estimated average marginal effects and 95% confidence intervals corresponding to the estimation of Equation (2.1) on our matched sample using an Ordered Logit model. Results correspond to the specification reported in Column (6) of Table 2.2 which controls for political ideology, regional fixed effects, time-fixed effects, the interaction of regional and time-fixed effects, and the variables used in the matching specification.

temporary contract reduces the likelihood of agreeing (Column 4), neither agreeing or disagreeing (Column 3), disagreeing (Column 2), and strongly disagreeing (Column 1) with the statement by 1.65, 1.34, 0.9, and 0.1 percentage points, respectively. The estimated AMEs do not statistically differ depending on the control varies included in the estimation.[30]

To determine the impact of holding a temporary contract on the likelihood of supporting different levels of redistribution preferences, the estimated AMEs must

[30]In Appendix C, Figure C.1 displays the estimated AMEs of the different specifications reported in Table 2.2.

Table 2.3.: Average Marginal Effects of Temporary Contract on Preferences for Redistribution

	(1) Strongly disagree	(2) Disagree	(3) Neither agree nor disagree	(4) Agree	(5) Strongly agree
(a) Marginal Effect	-0.002***	-0.009***	-0.013***	-0.016***	0.040***
(b) Pr(Pref=j|T=0)	0.010	0.056	0.105	0.488	0.341
(c) Effect in % = (a)/(b)	-16.566	-15.847	-12.813	-3.380	11.874

Notes: Average marginal effects corresponding to the estimation of Equation (2.1) on our matched sample using an Ordered Logit model. Results correspond to the specification reported in Column (6) of Table 2.2 which controls for political ideology, regional fixed effect, time-fixed effect, the interaction of regional and time fixed effects, and the individual characteristics included in the matching specification. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

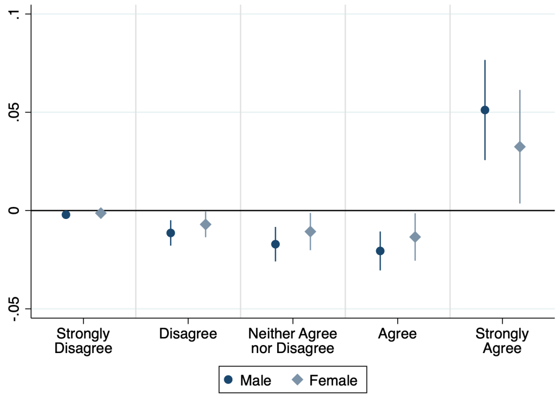
be evaluated relative to the baseline probability of supporting each redistribution level. In Table 2.3, row (b) presents the baseline probability of an individual with a permanent contract (T=0) reporting a specific preference for redistribution, while holding all other variables constant at their mean values. As shown in row (b), individuals with a permanent contract have a 34.1% probability of strongly agreeing (Column 5) and a 48.8% probability of agreeing (Column 4) with redistribution. The last row of Table 2.3 combines both measures and shows that holding a temporary contract increases the likelihood of an individual strongly agreeing with reducing income differences by 11.8% while reducing the likelihood of supporting any of the other categories. Overall, these results suggest that the effect of the contract type on determining individuals' redistribution preferences is quite substantial in its magnitude.

2.5.2. Heterogeneous Effects based on Individual Characteristics

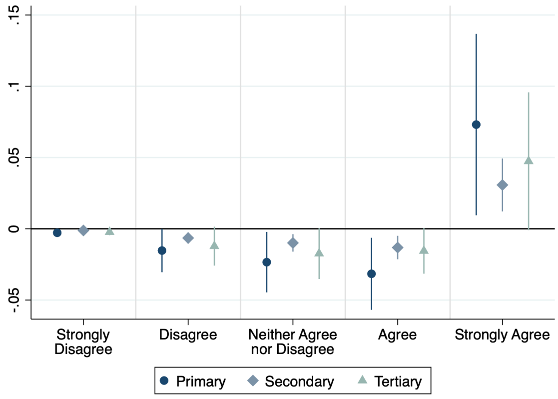
After reporting the average marginal effects of holding a temporary contract on preferences for redistribution, we report the results from analyzing heterogeneous effects based on individual characteristics in this section. More specifically, we study whether the impact of economic uncertainty associated with temporary contracts plays a different role in determining redistribution preferences depending on gender, education level, and age of individuals.

Figure 2.7.: Average Marginal Effects of Temporary Contract on Preferences for Redistribution: Heterogeneous Effects based on Individual Characteristics

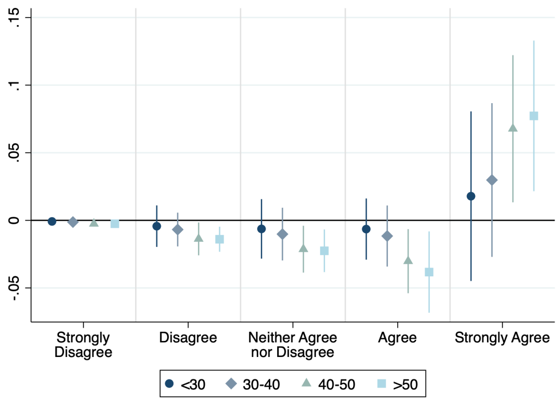
(a) Gender



(b) Education



(c) Age



Notes: Estimated average marginal effects and 95% confidence intervals corresponding to the estimation of Equation (2.1) on our matched sample using an Ordered Logit model. Results correspond to the specification which includes the interaction of the main dependent variable, *Temporary* with *Gender* (Panel a), *Education* (Panel b), and *Age* (Panel c). Each specification controls for political ideology, regional fixed effects, time-fixed effect, the interaction of regional and time-fixed effects, and the variables used in the matching specification.

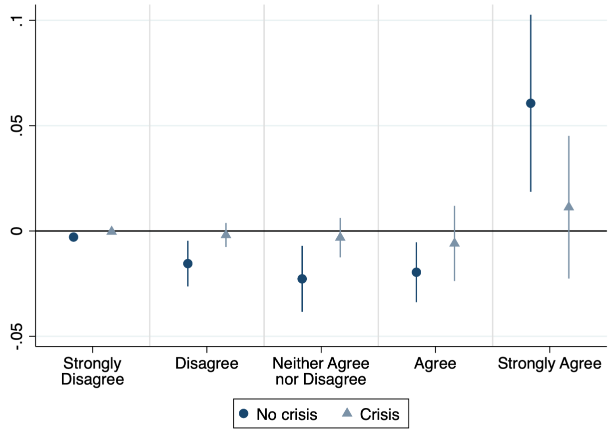
Figure 2.7 shows the heterogeneous average marginal effects.[31] Panel (a) reports heterogeneous effects based on individuals' gender. Differences in AMEs across genders are not statistically significant. Holding a temporary contract leads to a statistically significant increase in the probability of supporting the highest level of redistribution of 3.2 percentage points for women and 5.1 percentage points for men, while decreasing the probability of supporting lower levels of redistribution. These results align with our baseline results. Thus, once we control for the potential differential effect that gender has on the demand for redistribution, the effect of having a temporary contract on the demand for redistribution does not differ for men and women.

Panel (b) reports the marginal effects of holding a temporary contract depending on individuals' education level. Our results indicate that holding a temporary contract statistically increases the probability of agreeing with the highest level of redistribution while decreasing the probability of supporting any other level. More specifically, the fact of holding a temporary contract increases the probability of agreeing with the highest level of redistribution by 7.3 percentage points for individuals with at most primary education, 3.1 for individuals with secondary education, and 4.7 for individuals with tertiary education. Although the magnitude of the estimated effect is larger for individuals with primary education, these differences are not statistically significant.

Last, Panel (c) shows the average marginal effects of holding a temporary contract for different age groups. In this case, our results document differential effects which align with the idea that temporary contracts affect individuals' perception of economic uncertainty differently during their lifetime. Our results show that holding a temporary contract does not impact preferences for income redistribution for individuals below 40, when, in principle, these contracts are more likely to be perceived as a stepping stone in the labor market. However, for individuals aged between 40 and 50 and those aged above 50, the fact of holding a temporary contract statistically increases the probability of strongly agreeing with income redistribution and decreases the probability of supporting any of the other category. More specifically, holding a temporary contract increases the probability of supporting the highest level of redistribution by 6.8 for individuals aged between 40 and 50, and by 7.7 percentage points for those above 50. This result suggests that when temporary contracts are perceived as a dead end, they generate a higher perception of economic uncertainty.

[31]These AMEs correspond to the specification that controls for political ideology, the interaction of both regional and time-fixed effects, and the individual characteristics used in the matching specification. In Appendix C, Table C.1 reports the point estimates.

Figure 2.8.: Average Marginal Effects of Temporary Contracts on Preferences for Redistribution: Heterogeneous Effects based on the Macroeconomic Context



Notes: Estimated average marginal effects and 95% confidence intervals corresponding to the estimation of Equation (2.1) on our matched sample using and Ordered Logit model. Results correspond to the specification which includes the interaction of the main dependent variable, *Temporary*, with an indicator for economic environment ,*Crisis*, and controls for political ideology, regional fixed effects, time-fixed effects, the interaction of regional and time-fixed effects, and the individual characteristics used in the matching specification.

2.5.3. Heterogeneous Effects based on the Macroeconomic Environment

We further explore the role of economic uncertainty in determining redistribution preferences by analyzing heterogeneous effects of the contract type depending on the macroeconomic context. We define the variable *Crisis* to take a value one for years of high economic crisis and economic instability.[32] By doing so, we are able to identify whether the economic uncertainty generated by the labor market is different depending on the macroeconomic context.

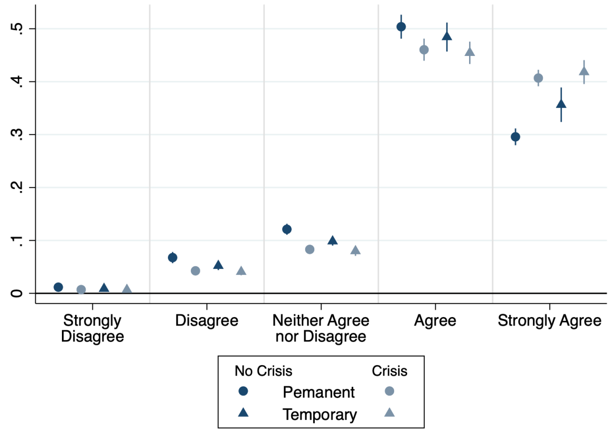
Figure 2.8 shows the estimated marginal effects of holding a temporary contract for different macroeconomic situations. During periods of economic stability, holding a temporary contract increases the probability of strongly agreeing with redistribution by 6.1 percentage points and decreases the probability of supporting any other redistribution level. However, this effect disappears in periods of economic crisis.[33]

To extend on the results presented above, Figure 2.9 plots the predicted values of supporting each redistribution level depending on the macroeconomic context. Coefficients represented by a circle correspond to permanent workers, and triangles correspond to temporary workers. These results show that, in times of economic

[32]We exploit the 2008 financial crisis. Therefore, *Crisis* takes a value of one for survey waves from 2010 to 2016.

[33]In Appendix C, Table C.1 reports the point estimates.

Figure 2.9.: Predicted Probabilities of Support for Redistribution: Heterogeneous Effects based on the Macroeconomic Context



Notes: Predicted probabilities of support for redistribution corresponding to the estimation of Equation (2.1) on the matched sample. Specification includes the interaction of the main dependent variable, *Temporary* with an indicator for economic environment *Crisis*. Results corresponding to the specification which controls for political ideology, the interaction of regional fixed effects with the economic environment indicator, and the individual characteristics used in the matching process.

crisis, the predicted probability of strongly agreeing with redistribution is around 41% for all types of workers, and therefore there are no statistical differences depending on the type of contract. However, in times of no crisis there is a large and statistically significant difference between the predicted probability of strongly agreeing with redistribution. In times of no crisis 29% of workers with a permanent contract strongly agree with redistribution, while this share is 37% among workers with temporary contracts. Thus, the null marginal effect of the contract type in times of crisis is due to a larger increase in the support for redistribution relative to their support in times of no crisis by workers with permanent contracts than that experienced by workers with temporary contracts.

These results align with the hypothesis that individual preferences for income redistribution follow a social insurance approach. In periods of economic stability, the economic uncertainty linked to holding a temporary contract implies stronger preferences for redistribution of temporary workers. However, when large increases in unemployment rates extend economic instability beyond the contract type, permanent workers exhibit a large increase in redistribution preferences which positions them at the same level as temporary workers.

Our results are consistent with previous literature studying the effect of economic shocks on political attitudes.[34] These studies show that personal experience of

[34]Economic shocks are defined as an instance of a significant and intense change in one's personal economic standing, whether realized through a job loss or expected through a sharp increase in the likelihood of being laid off (Margalit, 2019).

economic shocks tends to significantly impact individuals' political attitudes and redistribution preferences even if they dissipate over time (Margalit, 2013, 2019). As general preferences are determined by the number of people that net benefit from social policy (Rehm, 2011) and the effect of inequality depends on to whom benefits are targeted (Moene and Wallerstein, 2001), the impact of economic shocks in dual contexts is especially relevant. Our results show that in this context, expansions of labor market risk beyond the contract type imply an increase in the homogeneity of the risk pool and a reduction in the social distance between worker groups leading to a generalized increase in aggregate redistribution demand.

2.5.4. Robustness Checks

In this section we present several robustness tests to guarantee the causal interpretation and stability of our results. First, we show that our results are robust to include further variables in our matching specification and additional control variables. Second, we show that our results do not depend on the specification used in the estimations.

Alternative Matching Specifications

As stated previously, the variables used in the matching process correspond to those individual characteristics that have an impact both in determining the fact of holding a temporary contract and on redistribution preferences. A potential concern could be that our baseline results could be biased due to the omission of relevant variables in the matching implemented, such as differences in economic structure across regions or individual's income level.

Ideally, to identify the effect of the contract type on redistribution preferences, we would want to compare individuals that, besides being similar on the characteristics used in our base matching specification, live in the same (or similar) region and have the same income level. As discussed in previous sections, even though these variables might influence individual preferences, we do not include them in our matching specification to prevent an increase in strata that would bring a substantial loss of observations.[35] In this section, we further prove the validity of our baseline matching specification by showing that results are robust when we perform the

[35]The income variable is not homogeneously defined across surveys. To compare income levels over surveys, we create a variable categorizing individuals into three income brackets. The first bracket includes individuals with a yearly income of less than 12,000 euros, the second includes individuals with a yearly income from 12,000 to 30,000 euros, and the third bracket includes individuals with an income of more than 30,000 euros per year.

matching process at the region level or when we include income in the matching specification.[36]

Table 2.4.: Effect of Temporary Contract on Preferences for Redistribution: Alternative Matching Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
			(a) Matching at the Regional Level			
Temporary	0.240***	0.208***	0.213***	0.213***	0.215***	0.213***
	(0.056)	(0.057)	(0.057)	(0.056)	(0.058)	(0.059)
Pol. Ideology		-0.134***	-0.131***	-0.129***	-0.127***	-0.127***
		(0.032)	(0.033)	(0.034)	(0.035)	(0.034)
N	3,687	3,687	3,687	3,687	3,687	3,687
			(b) Matching with Income			
Temporary	0.190**	0.167**	0.149*	0.157**	0.190**	0.189***
	(0.084)	(0.081)	(0.084)	(0.078)	(0.074)	(0.068)
Pol. Ideology		-0.137***	-0.137***	-0.132***	-0.136***	-0.132***
		(0.032)	(0.033)	(0.033)	(0.033)	(0.030)
N	4,279	4,279	4,279	4,279	4,279	4,279
RFE	NO	NO	YES	YES	YES	YES
TFE	NO	NO	NO	YES	YES	YES
RFE*TFE	NO	NO	NO	NO	YES	YES
Controls	NO	NO	NO	NO	NO	YES

Notes: Results from estimating Equation (2.1) using an Ordered Logit model on the sample matched at the regional level (Panel a) and at the income level (Panel b). In addition to region or income, the matching is performed on individuals' gender, age, education level, minority status, and previous unemployment status. Controls include regional fixed effects, time-fixed effect, the interaction of region and time-fixed effects, and the individual characteristics used in the matching process. Standard errors clustered at the region level are in parenthesis. * $p < 0.10$, ** $p<0.05$, *** $p< 0.01$.

Table 2.6 presents the results from estimating Equation (2.1) under these two alternative matching specifications. Panel (a) reports the effect of the contract type on preferences for income redistribution when, in addition to the individual characteristics used in our baseline approach, we include the region in the matching specification. Similarly, Panel (b) reports the coefficients corresponding to the matched sample when we match individuals based on income level.[37] In both alternative specifications, positive and statistically significant coefficients indicate an

[36]When we perform matching at the regional level, the matched sample is reduced to 3,687 observations. When we include income in the matching specification the final sample is reduced to 4,279 observations.

[37]Appendix D contains additional material on differences in means and distribution of redistribution preferences before and after matching for each alternative specification.

increase in redistribution preferences derived from holding a temporary contract. This result remains stable when controlling for individuals' political ideology (Column 2), adding regional fixed effects (Column 3), time-fixed effects (Column 4), the interaction of both fixed effects (Column 5), and the variables used in the matching specification (Column 6).

Table 2.5.: Average Marginal Effects of Temporary Contract on Preferences for Redistribution: Alternative Matching Specifications

	(1) Strongly disagree	(2) Disagree	(3) Neither agree nor disagree	(4) Agree	(5) Strongly agree
(i) Baseline Matching					
(a) Marginal Effect	-0.002***	-0.009***	-0.013***	-0.016***	0.040***
(b) Pr(Pref=j|T=0)	0.010	0.056	0.105	0.488	0.341
(c) Effect in % = (a)/(b)	-16.566	-15.847	-12.813	-3.380	11.874
(ii) Matching at the Regional Level					
(a) Marginal Effect	-0.002***	-0.010***	-0.015***	-0.019***	0.045***
(b) Pr(Pref=j|T=0)	0.010	0.054	0.104	0.503	0.329
(c) Effect in % = (a)/(b)	-18.173	-18.101	-14.398	-3.761	13.791
(iii) Matching with Income					
(a) Marginal Effect	-0.001***	-0.010***	-0.013***	-0.016***	0.040***
(b) Pr(Pref=j|T=0)	0.009	0.062	0.100	0.466	0.363
(c) Effect in % = (a)/(b)	-16.222	-15.514	-12.954	-3.473	11.079

Notes: Estimated average marginal effects from estimating Equation (2.1) using and Ordered Logit model. Panel (a) shows the results from estimating Equation (2.1) on the sample matched at the regional level. Panel (b) shows the results from estimating Equation (2.1) on the sample matched including income in the matching specification. Results correspond to the specification reported in Table 2.6, Column (6), which includes political ideology, time-fixed effects, regional fixed effects, their interaction, and the individual characteristics used in the matching process. * $p < 0.10$, ** $p<0.05$, *** $p< 0.01$.

Table 2.5 reports the AMEs and their value relative to the baseline probability of supporting each redistribution level on the two alternative matching specifications.[38] This table corroborates that the estimated effect of holding a contract type is quantitatively very similar when implementing these two other matching. In our baseline matching specification, holding a temporary contract increases the probability of agreeing with the highest level of redistribution by 4.05 percentage points. This marginal effect is 4.5 when the matching is implemented within regions, and 4.02 when we match on income. The relative importance relative to the baseline probability of supporting each redistribution level is also very similar and stable in magnitude in all the other categories.

The analysis presented in this section further validates the effect of the contract

[38]In Appendix D, Figure D.3 plots these AMEs.

type in shaping individual redistribution preferences as it shows that our baseline results are not biased by omitting potential relevant variables such as income or region in the matching specification. This is an expected result given that our baseline matching includes the main predictors of income (age, gender, and education) and our estimations include regional fixed effects.

In this line of reasoning, as a further robustness analysis we estimate the AMEs of having a temporary contract while including in the regressions two additional variables that could potentially affect our results. The main activity of the individual and the economic sector where they work can potentially affect both the contract type and the preferences for redistribution.[39] In Appendix C we report the results of performing the matching considering only individuals whose main activity is paid work. The results are qualitatively identical to our baseline results.

Binary Preferences

To corroborate that our results do not depend on the functional form used in our regressions, we recode the dependent variable into a binary variable and estimate a linear probability model. As discussed above, more than 80% of the respondents are concentrated in the two highest levels of redistribution demand, which could be due to the desirability bias. To take this fact into account, we start by coding our measure of preferences for income redistribution to take the value of one only for those who strongly agree with the statement *"The government should take measures to reduce differences in income levels"* and zero otherwise. By doing so, we identify variation within those individuals with strong preferences for redistribution who, in principle, should not be subject to desirability bias in their answers.

Table 2.6 shows the results from estimating Equation (2.1) on our matched sample for this alternative definition of our dependent variable using a linear probability model.[40] Results reported in Column (5) show that holding a temporary contract increases the probability of supporting the strong demand for redistribution by 4.3 percentage points. This estimate is very similar to the one obtained in our Ordered Logit estimation (4.05).

As an additional robustness check, we also recode our redistribution demand variable to take the value of one if an individual "Agrees" or "Strongly Agrees" with redistribution. By doing so we estimate the effect of holding a temporary contract on having a positive demand for redistribution. The results show that having a temporary contract increases the probability of supporting redistribution although the effect

[39]We do not include these two variables in the matching for the substantial reduction that they generate in the final sample.

[40]In Appendix C, Table C.3 shows that the results are qualitatively the same when we estimate a Probit or a Logit model.

Table 2.6.: Effect of Temporary Contract on Strong Preferences for Redistribution: OLS estimation

	(1)	(2)	(3)	(4)	(5)	(6)
Temporary	0.052***	0.044**	0.038**	0.040***	0.043***	0.043***
	(0.017)	(0.016)	(0.014)	(0.013)	(0.013)	(0.013)
Pol. Ideology		-0.033***	-0.032***	-0.031***	-0.029***	-0.029***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
R-squared	0.003	0.022	0.031	0.053	0.098	0.103
N	6,984	6,984	6,984	6,984	6,984	6,984
RFE	NO	NO	YES	YES	NO	NO
TFE	NO	NO	NO	YES	NO	NO
RFE*TFE	NO	NO	NO	NO	YES	YES
Controls	NO	NO	NO	NO	NO	YES

Notes: Results from estimating Equation (2.1) on our baseline matched sample using an OLS model. The dependent variable is coded one if an individual "Strongly agrees" with redistribution, and zero otherwise. Controls include regional fixed effects, time-fixed effect, the interaction of both fixed effects and the individual characteristics used in the matching process. Standard errors clustered at the region level in parenthesis. * $p < 0.10$, ** $p<0.05$, *** $p< 0.010$.

has a smaller magnitude (2.4 percentage points).[41] These results further provide evidence in support of the social insurance approach. Holding a temporary contract not only increases the probability of strongly agreeing with redistribution, but leads to a general shift toward a positive demand. Our results show that having a temporary contract increases the probability of being located in one of the two highest levels of redistribution demand.

2.6. Conclusion

Institutions have an important role in determining the economic structure and inequality levels of societies. Labor market institutions are especially relevant as they can affect the risk faced by workers and, therefore, redistribution demand. In dual labor markets, different degrees of protection depending on the contract type generate a discontinuous distribution of risk across workers. Workers with temporary contracts have lower earnings and a higher unemployment probability than those with permanent contracts. Thus, if temporary contracts are not perceived as a stepping stone in the labor market, they can increase the perception of economic insecurity. When the redistributive function of the public sector is perceived as a social insurance, its demand should be stronger not only for those with lower income, but also for those facing higher economic uncertainty. In this study, we provide

[41] In Appendix C, Table C.4 shows these results.

evidence of the causal effect of holding a temporary contract on the demand for redistribution.

Our results show that workers with temporary contracts are 11% more likely to strongly agree that the government should reduce income inequality than workers with permanent contracts. We base our empirical strategy on a matching methodology to deal with the fact that the incidence of temporary contracts is stronger for workers with lower levels of education, younger workers, and women. By matching individuals based on individual characteristics determining both the probability of being subject to a temporary contract and redistribution preferences, we are able to isolate potential confounding effects and estimate the causal effect of being subject to a temporary contract on individual preferences for income redistribution.

We complement our analysis by studying whether the contract type affects redistribution preferences heterogeneously depending on individuals' age, gender, and education level. Our results show that temporary contracts increase redistribution preferences independently of individuals' gender or education. In terms of age, we show that the effect is mainly concentrated in individuals aged 40 and above. This result suggests that while younger individuals perceive temporary contracts as a stepping-stone into the job market, these contracts are perceived as a dead end for individuals over 40, leading to an increase in economic insecurity and, thus, a higher demand for redistribution.

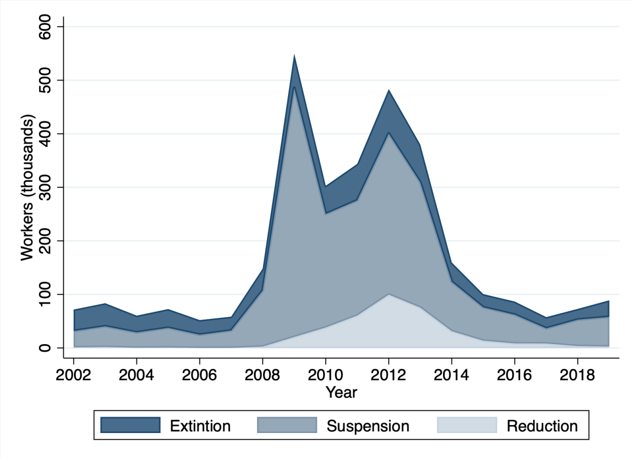
We provide further evidence of the role of economic uncertainty in determining redistribution demand by analyzing the differential effect of the contract type depending on the macroeconomic context. Our results show that in times of economic crisis, when economic risk extends across all workers, the effect of the contract type dissipates. Increases in the general level of economic risk lead to a more homogeneous risk distribution and significant increases in redistribution preferences of individuals with ex-ante more protected labor market positions. These results further contribute to previous work analyzing the effects of economic shock on redistribution preferences (Margalit, 2019).

Our results imply that significant gaps in employment protection and extensive use of temporary contracts lead to important differences in risk exposure across worker groups. If aggregated redistribution demand is determined by the risk perception of those in more protected positions, individuals holding temporary contracts are doubly disadvantaged. First, they face higher instability derived from low conversion rates into protected contracts (Güell and Petrongolo, 2007) and lower earnings (García-Pérez et al., 2018). Second, political support for those categories of social insurance that would benefit them is reduced as their insurance demand is underrepresented.

These results point to the need to design labor market institutions to mitigate labor market polarization and ensure an adequate level of social insurance independently of individuals' labor contracts. Policies reducing the employment protection gap between temporary and permanent workers, the creation of unified open-ended contracts with progressively increasing termination costs, or the limitation of temporary contracts for specific circumstances can help move toward this direction (see Bentolila et al. (2020) for a discussion of these alternatives). Although we provide strong evidence on the role of temporary contracts in defining redistribution preferences, an avenue left to study is how these preferences translate into voting behavior.

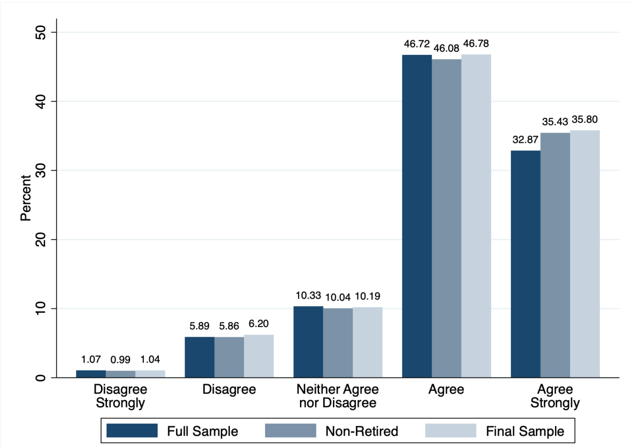
A. Descriptive

Figure A.1.: Workers Affected by Employment Regulation Procedures



Notes: Number of workers affected by employment regulation procedures by type of procedure. Administrative data from the Spanish Ministry of Labour and Social Economy.

Figure A.2.: Distribution of Preferences for Redistribution: Sample Restrictions



Notes: Percent of respondents for each category of preferences for income redistribution. Data corresponds to all survey waves from 2002 to 2018. *Full Sample* corresponds to all ESS respondents reporting information on preferences for income redistribution. *Non-Retired* corresponds to the sample which includes individuals active in the labor market aged 70 or below not reporting to be retired. *Final Sample* corresponds to the sample which includes individuals active in the labor market aged 70 or below not reporting to be retired who answered all the questions used in the analysis.

Table A.1.: Variables Definition and Summary Statistics

Variable	Definition	(a) Before Matching (N=7,727)		(b) After Matching (N=6,984)	
		Mean	St. Dev	Mean	St. Dev
PrefRedist	Question (1-5): 1: Strongly Disagree 2: Disagree 3: Neither Agree nor Disagree 4: Agree 5: Strongly Agree	4.101	0.889	4.125	0.859
Temporary	Dummy variable 0: Permanent Contract 1: Temporary Contract	0.336	0.472	0.348	0.476
Gender	Dummy variable 0: Male 1: Female	0.492	0.500	0.548	0.498
Left-Right	Question (1-10): 0: Left, 1: Right	4.264	2.064	4.277	2.064
Education	Highest level of education achieved				
	1: Lower than secondary	0.150	0.357	0.159	0.366
	2: Secondary, lower than tertiary	0.571	0.495	0.635	0.482
	3: Tertiary	0.279	0.448	0.206	0.404
Age	Age of the respondent in years	41.018	12.001	36.935	11.617
Age Grouped	Age of the respondent in categories				
	1: 14-29 years	0.200	0.400	0.347	0.476
	2: 30-39 years	0.270	0.444	0.275	0.446
	3: 40-49 years	0.261	0.439	0.211	0.408
	4: 50-59 years	0.198	0.399	0.130	0.337
	5: 60-75 years	0.071	0.256	0.036	0.187
Unemployed	Dummy variable 1: Has been unemployed and seeking for work for a period of 12 months or more	0.240	0.427	0.333	0.471
Minority	Dummy variable 1: Respondent belongs to a minority ethnic group in Spain	0.024	0.154	0.014	0.118

Notes: Definition of the main variables used in the analysis. Summary statistics based on our final sample which includes working individuals aged 70 or below with information on all the variables used in the analysis. Panel (a) corresponds to the final sample before matching. Panel (b) corresponds to the sample after the baseline matching.

B. Baseline Matching

Table B.1.: Determinants of Contract Type. Probit Estimation of Variables used in the Baseline Matching Approach

	(1)	(2)	(3)
Female	0.229***	0.231***	0.236***
	(0.032)	(0.032)	(0.032)
Unemployed	0.730***	0.710***	0.697***
	(0.036)	(0.037)	(0.038)
Minority	0.431***	0.429***	0.482***
	(0.098)	(0.098)	(0.099)
Education (base primary)			
Secondary	-0.422***	-0.455***	-0.420***
	(0.047)	(0.048)	(0.049)
Tertiary	-0.706***	-0.738***	-0.687***
	(0.053)	(0.054)	(0.055)
Age (base <30)			
30-39	-0.768***	-0.774***	-0.788***
	(0.044)	(0.045)	(0.045)
40-49	-1.091***	-1.111***	-1.125***
	(0.047)	(0.047)	(0.048)
50-59	-1.346***	-1.382***	-1.378***
	(0.053)	(0.054)	(0.054)
>60	-1.535***	-1.583***	-1.577***
	(0.078)	(0.079)	(0.080)
Constant	0.520***	0.590***	0.880***
RFE	NO	YES	YES
TFE	NO	NO	YES
N	7,727	7,727	7,727
Pseudo-R2	0.142	0.145	0.158

Notes: Dependent variable, *Temporary*, is a dummy equal to one if the contract is temporary and zero if the contract is permanent. The model is estimated on our final sample which includes working individuals aged 70 or below with information on all variables used in the matching specification. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

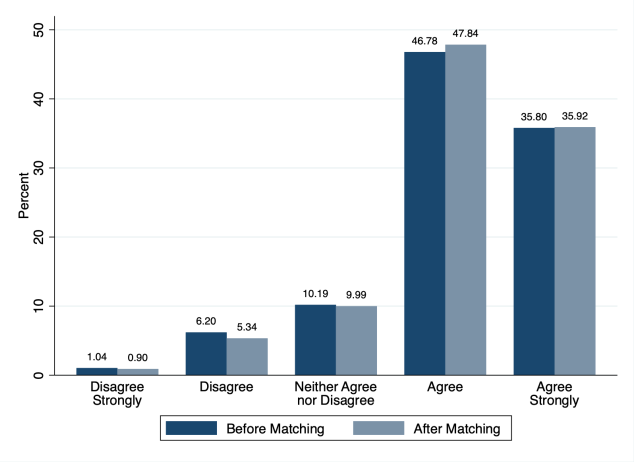
Table B.2.: Baseline Matching: Multivariate L1 Distance. Matched and Unmatched Samples

(a) Unmatched Sample (N=7,727)						
		Distribution				
	L1 distance	min	25%	50%	75%	max
Gender	0.081	0	0	1	0	0
Education	0.111	0	0	0	-1	0
Age	0.244	0	-1	-1	-1	0
Unemployed	0.180	0	0	0	1	0
Minority	0.021	0	0	0	0	0
Year	0.034	0	0	0	0	0
Multivariate L1 distance			0.436			

(b) Matched Sample (N=6,984)						
		Distribution				
	L1 distance	min	25%	50%	75%	max
Gender	0.000	0	0	0	0	0
Education	0.000	0	0	0	0	0
Age	0.000	0	0	0	0	0
Unemployed	0.000	0	0	0	0	0
Minority	0.000	0	0	0	0	0
Year	0.000	0	0	0	0	0
Multivariate L1 distance			2.96E-15			

Notes: Multivariate L1 distance statistics and differences within the distribution of each variable used in the baseline matching. Data corresponds to our final sample, which includes working individuals aged 70 or below with information on all variables used in the baseline matching. Panel (a) corresponds to measures before matching. Panel (b) corresponds to our matched sample.

Figure B.1.: Distribution of Preferences for Redistribution: Before and After Baseline Matching

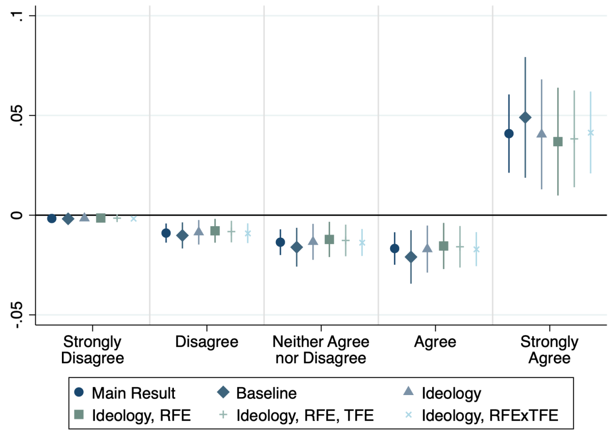


Notes: Percent of respondents for each category of preferences for income redistribution. *"Before Matching"* represents the distribution before matching and corresponds to our final sample, which includes working individuals aged 70 or below with information on all variables used in the matching. *"After Matching"* corresponds to the distribution on the matched sample.

C. Additional Material

C.1. Baseline Results

Figure C.1.: Average Marginal Effect of Temporary Contract on Preferences for Redistribution: Alternative Specifications



Notes: Estimated average marginal effects and 95% confidence intervals corresponding to the estimation of Equation (2.1) on our matched sample using an Ordered Logit model. Marginal effects correspond to the specifications reported in Table 2.2, *"Baseline"* corresponds to Column (1), *"Ideology"* to Column (2), *"Ideology, RFE"* to Column (3), *"Ideology, RFE, TFE"* to Column (4), *"Ideology, RFExTFE"* to Column (5), and *"Main Result"* to Column (6).

C.2. Heterogeneous Effects

Table C.1.: Heterogeneous Average Marginal Effects of Temporary Contract on Preferences for Redistribution

	(1) Strongly Disagree	(2) Disagree	(3) Neither Agree nor Disagree	(4) Agree	(5) Strongly Agree
Gender					
Male	-0.002***	-0.011***	-0.017***	-0.021***	0.051***
	(0.001)	(0.003)	(0.004)	(0.005)	(0.013)
Female	-0.001**	-0.007**	-0.011**	-0.013**	0.032**
	(0.001)	(0.003)	(0.005)	(0.006)	(0.015)
Education					
Primary	-0.003**	-0.015**	-0.023**	-0.032**	0.073**
	(0.001)	(0.008)	(0.011)	(0.013)	(0.032)
Secondary	-0.001***	-0.006***	-0.010***	-0.013***	0.031***
	(0.000)	(0.002)	(0.003)	(0.004)	(0.009)
Tertiarty	-0.002**	-0.012*	-0.017*	-0.016*	0.047*
	(0.001)	(0.007)	(0.009)	(0.008)	(0.025)
Age					
Below 30	-0.001	-0.004	-0.006	-0.006	0.018
	(0.001)	(0.008)	(0.011)	(0.012)	(0.032)
30 to 40	-0.001	-0.007	-0.010	-0.012	0.030
	(0.001)	(0.006)	(0.010)	(0.012)	(0.029)
40 to 50	-0.003**	-0.014**	-0.021**	-0.030**	0.068**
	(0.001)	(0.006)	(0.009)	(0.012)	(0.028)
More than 50	-0.003***	-0.014***	-0.023***	-0.038**	0.077***
	(0.001)	(0.005)	(0.008)	(0.015)	(0.028)
Macroeconomic Environment					
Crisis	-0.000	-0.002	-0.003	-0.006	0.011
	(0.000)	(0.003)	(0.005)	(0.009)	(0.017)
No Crisis	-0.003***	-0.015***	-0.023***	-0.020***	0.061***
	(0.001)	(0.006)	(0.008)	(0.007)	(0.021)
N	6,984	6,984	6,984	6,984	6,984

Notes: Estimated average marginal effects corresponding to the estimation of Equation (2.1) on our matched sample using an Ordered Logit model. Results correspond to the specification which includes regional and time-fixed effects, the interaction of both fixed effects and controls for political ideology, and the individual characteristics included in the marching specification. Standard errors are clustered at the regional level in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

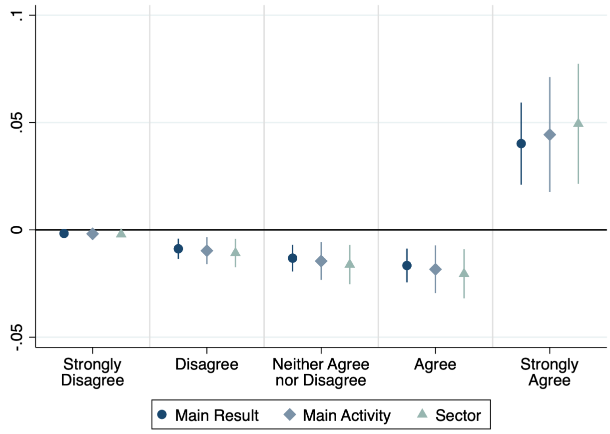
C.3. Additional Controls

Table C.2.: Effect of Temporary Contract on Preferences for Redistribution: Additional Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temporary	0.204***	0.172***	0.158***	0.168***	0.190***	0.189***	0.209***	0.234***
	(0.065)	(0.061)	(0.059)	(0.054)	(0.047)	(0.046)	(0.064)	(0.067)
Pol. Ideology		-0.144***	-0.142***	-0.138***	-0.137***	-0.138***	-0.138***	-0.139***
		(0.020)	(0.021)	(0.021)	(0.020)	(0.019)	(0.018)	(0.019)
N	6,883	6,883	6,883	6,883	6,883	6,883	6,883	6,883
RFE	NO	NO	YES	YES	YES	YES	YES	YES
TFE	NO	NO	NO	YES	YES	YES	YES	YES
RFE*TFE	NO	NO	NO	NO	YES	YES	YES	YES
Matching Variables	NO	NO	NO	NO	NO	YES	YES	YES
Main Activity	NO	NO	NO	NO	NO	NO	YES	YES
Sector	NO	NO	NO	NO	NO	NO	NO	YES

Note: Results from estimating Equation (2.1) on our base matched sample. Coefficients corresponding to the estimation of an Ordered Logit model. The dependent variable, *PrefRedist*, corresponds to our measure of preferences for redistribution. Standard errors clustered at the regional level are in parenthesis. * p < 0.10, ** p < 0.05, *** p < 0.01.

Figure C.2.: Average Marginal Effect of Temporary Contract on Preferences for Redistribution: Additional Controls



Notes: Estimated average marginal effects and 95% confidence intervals corresponding to the estimation of Equation (2.1) on our matched sample using an Ordered Logit model. Results correspond to the specifications reported in Table C.2. *"Main Result"* corresponds to the specification reported in Column (6), which controls for political ideology, regional fixed effects, time-fixed effects, the interaction of regional and time-fixed effects, and the variables used in the matching; *"Main Activity"* corresponds to the specification reported in Column (7) and adds individual's main activity as a control; *"Sector"* corresponds to the specification reported in Column (8) and adds the sector in which an individual works as a control.

C.4. Binary Preferences

Table C.3.: Effect of Temporary Contract on Strong Preferences for Redistribution: Alternative Probability Models.

	(1)	(2)	(3)	(4)	(5)	(6)
a) *Logit*						
Temporary	0.224***	0.195***	0.168***	0.180***	0.203***	0.205***
	(0.070)	(0.068)	(0.062)	(0.057)	(0.058)	(0.057)
Pol. Ideology		-0.146***	-0.145***	-0.142***	-0.138***	-0.138***
		(0.025)	(0.026)	(0.026)	(0.027)	(0.026)
Marginal effect	0.050***	0.042***	0.035***	0.038***	0.041***	0.042***
b) *Probit*						
Temporary	0.138***	0.121***	0.104***	0.113***	0.128***	0.130***
	(0.044)	(0.042)	(0.038)	(0.034)	(0.035)	(0.035)
Pol. Ideology		-0.089***	-0.088***	-0.085***	-0.082***	-0.082***
		(0.015)	(0.016)	(0.015)	(0.016)	(0.015)
Marginal effect	0.049***	0.042***	0.035***	0.037***	0.040***	0.040***
N	6,984	6,984	6,984	6,984	6,944	6,944
RFE	NO	NO	YES	YES	NO	NO
TFE	NO	NO	NO	YES	NO	NO
RFE*TFE	NO	NO	NO	NO	YES	YES
Controls	NO	NO	NO	NO	NO	YES

Notes: Results from estimating Equation (2.1) on our baseline matched sample using a Logit model (Panel a), and a Probit model (Panel b). The dependent variable is coded as one if an individual "Strongly agrees" with redistribution, and zero otherwise. Controls include the individual characteristics used in the matching process. Standard errors clustered at the region level in parenthesis. * p<0.10, ** p<0.005, *** <0.010.

Table C.4.: Effect of Temporary Contract on Strong Preferences for Redistribution: Alternative Probability Models.

	(1)	(2)	(3)	(4)	(5)	(6)
a) OLS						
Temporary	0.024**	0.020**	0.021**	0.022**	0.024**	0.024**
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Pol. Ideology		-0.017***	-0.017***	-0.016***	-0.015***	-0.016***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
b) *Logit*						
Temporary	0.180**	0.153**	0.160**	0.165**	0.184**	0.184**
	(0.072)	(0.069)	(0.072)	(0.069)	(0.073)	(0.076)
Pol. Ideology		-0.122***	-0.124***	-0.120***	-0.121***	-0.124***
		(0.033)	(0.034)	(0.036)	(0.038)	(0.038)
Marginal effect	0.024**	0.021**	0.021**	0.022**	0.024**	0.024**
c) *Probit*						
Temporary	0.099**	0.086**	0.089**	0.087**	0.088**	0.090**
	(0.040)	(0.038)	(0.041)	(0.038)	(0.041)	(0.043)
Pol. Ideology		-0.068***	-0.068***	-0.066***	-0.067***	-0.067***
		(0.019)	(0.019)	(0.020)	(0.021)	(0.021)
Marginal effect	0.024**	0.021**	0.021**	0.021**	0.020**	0.021**
N	6,984	6,984	6,984	6,984	6,984	6,984
RFE	NO	NO	YES	YES	NO	NO
TFE	NO	NO	NO	YES	NO	NO
RFE*TFE	NO	NO	NO	NO	YES	YES
Controls	NO	NO	NO	NO	NO	YES

Notes: Results from estimating Equation (2.1) on our baseline matched sample using an OLS model (Panel a), a Logit model (Panel b), and a Probit model (Panel c). The dependent variable is coded as one if an individual "Strongly agrees" or "Agrees" with redistribution, and zero otherwise. Controls include the individual characteristics used in the matching process. Standard errors clustered at the region level in parenthesis. * $p<0.10$, ** $p<0.005$, *** <0.010.

C.5. Alternative Sample Definition: Individuals with Paid Work as a Main Activity

Table C.5.: Baseline Matching in Alternative Sample Definition: Multivariate L1 Distance. Matched and Unmatched Samples

(b) Unmatched Sample (N=5,586)						
		Distribution				
	L1 distance	min	25%	50%	75%	max
Gender	0.056	0	0	0	0	0
Education	0.076	0	0	0	0	0
Age	0.262	0	-1	-1	-1	0
Unemployed	0.118	0	0	0	1	0
Minority	0.021	0	0	0	0	0
Year	0.064	0	0	0	0	0
Multivariate L1 distance	0.429					
(b) Matched Sample (N=4,744)						
		Distribution				
	L1 distance	min	25%	50%	75%	max
Gender	0.000	0	0	0	0	0
Education	0.000	0	0	0	0	0
Age	0.000	0	0	0	0	0
Unemployed	0.000	0	0	0	0	0
Minority	0.000	0	0	0	0	0
Year	0.000	0	0	0	0	0
Multivariate L1 distance	2.49E-15					

Note: Multivariate L1 distance statistics and differences within the distribution of each variable used in the baseline matching specification. Data corresponds to working individuals aged 70 or below with information on all variables used in the baseline matching and who report to have paid work as a main activity. Panel (a) corresponds to measures before matching. Panel (b) corresponds to the matched sample.

Table C.6.: Effect of Temporary Contract on Preferences for Redistribution: Alternative Sample Definition

	(1)	(2)	(3)	(4)	(5)	(6)
Temporary	0.328***	0.315***	0.289***	0.301***	0.328***	0.327***
	(0.070)	(0.065)	(0.064)	(0.055)	(0.048)	(0.051)
Pol. Ideology		-0.148***	-0.143***	-0.143***	-0.144***	-0.144***
		(0.025)	(0.026)	(0.028)	(0.029)	(0.028)
N	4,744	4,744	4,744	4,744	4,744	4,744
RFE	NO	NO	YES	YES	YES	YES
TFE	NO	NO	NO	YES	YES	YES
RFE*TFE	NO	NO	NO	NO	YES	YES
Controls	NO	NO	NO	NO	NO	YES

Note: Results from estimating Equation (2.1) on the matched sample of individuals aged 70 or below who report their main activity to be paid work and have information on all the variables used in the baseline matching specification. Coefficients corresponding to the estimation of an Ordered Logit model. The dependent variable, *PrefRedist*, corresponds to our measure of preferences for income redistribution. Standard errors clustered at the regional level are in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.7.: Average Marginal Effects of Temporary Contract on Preferences for Redistribution: Alternative Sample Definition

	(1) Strongly disagree	(2) Disagree	(3) Neither agree nor disagree	(4) Agree	(5) Strongly agree
(a) Marginal Effec	-0.00251***	-0.0155***	-0.0224***	-0.0274***	0.0678***
(b) Pr(Pref=j|T=0)	0.009	0.060	0.106	0.507	0.318
Effect in % = (a) / (b)	-27.402	-25.954	-21.051	-5.407	21.321

Notes: Average marginal effects corresponding to the estimation of the model defined by Equation (2.1). Results correspond to the specification reported in Column (6) of Table C.6 which includes regional fixed effects, time fixed effects, their interaction, and controls for political ideology and the individual characteristics included in the matching specification. Analysis performed on the matched sample of individuals aged 70 or below who report their main activity to be paid work and have information on all the variables used in the baseline matching specification.

D. Matching: Robustness

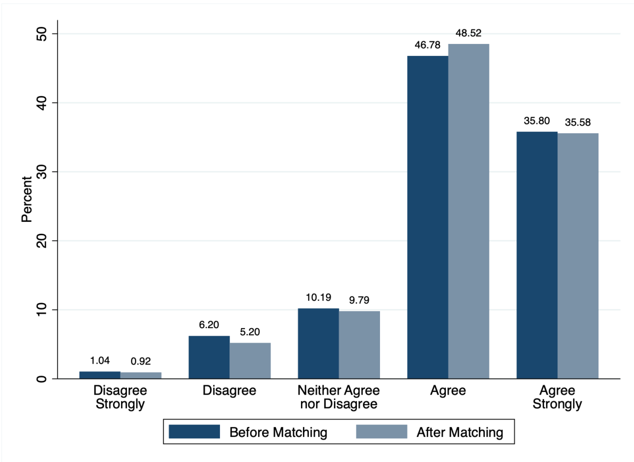
D.1. Matching at the Regional Level

Table D.1.: Matching at the Regional Level: Multivariate L1 Distance. Matched and Unmatched Samples

(b) Unmatched Sample (N=7,727)						
		Distribution				
	L1 distance	min	25%	50%	75%	max
Gender	0.081	0	0	1	0	0
Education	0.111	0	0	0	-1	0
Age	0.244	0	-1	-1	-1	0
Unemployed	0.180	0	0	0	1	0
Minority	0.021	0	0	0	0	0
Year	0.034	0	0	0	0	0
Region	0.133	0	-3	0	-1	0
Multivariate L1 distance			0.674			
(b) Matched Sample (N=4,040)						
		Distribution				
	L1 distance	min	25%	50%	75%	max
Gender	0.000	0	0	0	0	0
Education	0.000	0	0	0	0	0
Age	0.000	0	0	0	0	0
Unemployed	0.000	0	0	0	0	0
Minority	0.000	0	0	0	0	0
Year	0.000	0	0	0	0	0
Region	0.000	0	0	0	0	0
Multivariate L1 distance			2.34E-15			

Notes: Multivariate L1 distance statistics and differences within the distribution of each variable used in the matching specification including region. Data corresponds to our final sample, which includes working individuals aged 70 or below with information on all variables used in the baseline matching. Panel (a) corresponds to measures before matching. Panel (b) corresponds to our matched sample.

Figure D.1.: Distribution of Preferences for Redistribution: Before and After Matching at the Regional Level



Notes: Distribution of preferences for redistribution. Matching specification including region. *"Before Matching"* represents the distribution before matching and corresponds to our final sample, which includes working individuals aged 70 or below with information on all variables used in the matching. *"After Matching"* corresponds to the distribution on the matched sample.

D.2. Matching By Income

Table D.2.: Determinants of Contract Type. Probit Estimation of Variables used in the Matching Approach with Income

	(1)	(2)	(3)
Gender	0.183***	0.185***	0.191***
	(0.037)	(0.037)	(0.037)
Unemployed	0.666***	0.649***	0.644***
	(0.042)	(0.042)	(0.043)
Minority	0.386***	0.373***	0.423***
	(0.114)	(0.114)	(0.115)
Education (base primary)			
Secondary	-0.300***	-0.328***	-0.307***
	(0.054)	(0.055)	(0.056)
Tertiary	-0.452***	-0.481***	-0.452***
	(0.063)	(0.064)	(0.065)
Age (base <30)			
30-39	-0.813***	-0.810***	-0.820***
	(0.052)	(0.053)	(0.053)
40-49	-1.101***	-1.111***	-1.128***
	(0.055)	(0.055)	(0.056)
50-59	-1.352***	-1.377***	-1.378***
	(0.062)	(0.063)	(0.063)
>60	-1.564***	-1.591***	-1.592***
	(0.090)	(0.091)	(0.092)
Income (base $<12,000$)			
12,000 to 30,000	-0.504***	-0.527***	-0.500***
	(0.050)	(0.050)	(0.051)
$>30,000$	-0.912***	-0.936***	-0.879***
	(0.061)	(0.062)	(0.063)
Constant	0.957***	0.936***	1.182***
	(0.075)	(0.095)	(0.102)
RFE	NO	YES	YES
TFE	NO	NO	YES
N	5,991	5,991	5,991
Pseudo-R2	0.167	0.170	0.182

Notes: Dependent variable, *Temporary*, is a dummy equal to one if the contract is temporary and zero if the contract is permanent. The model is estimated on our final sample, which includes working individuals aged 70 or below with information on all variables used in our baseline matching specification and report information on income level. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

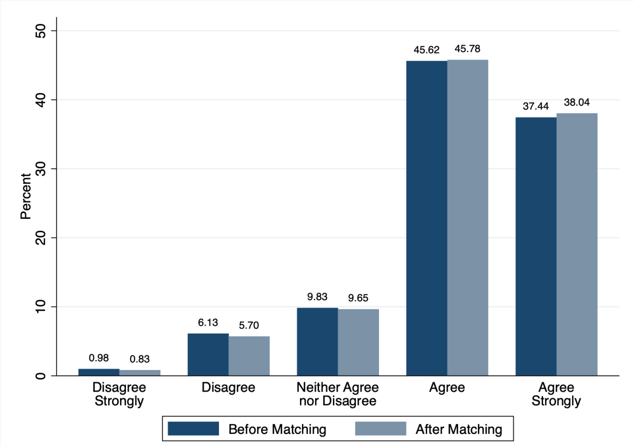
Table D.3.: Matching with Income: Multivariate L1 Distance. Matched and Unmatched Samples

(b) Unmatched Sample (N=5,991)						
		Distribution				
	L1 distance	min	25%	50%	75%	max
Gender	0.070	0	0	1	0	0
Education	0.121	0	0	0	-1	0
Age	0.225	0	-1	-1	-1	0
Unemployed	0.195	0	0	0	1	0
Minority	0.023	0	0	0	0	0
Year	0.040	0	0	0	0	0
Income	0.176	0	-1	0	-1	0
Multivariate L1 distance			0.531			

(b) Matched Sample (N=4,040)						
		Distribution				
	L1 distance	min	25%	50%	75%	max
Gender	0.000	0	0	0	0	0
Education	0.000	0	0	0	0	0
Age	0.000	0	0	0	0	0
Unemployed	0.000	0	0	0	0	0
Minority	0.000	0	0	0	0	0
Year	0.000	0	0	0	0	0
Income	0.000	0	0	0	0	0
Multivariate L1 distance			4.18E-15			

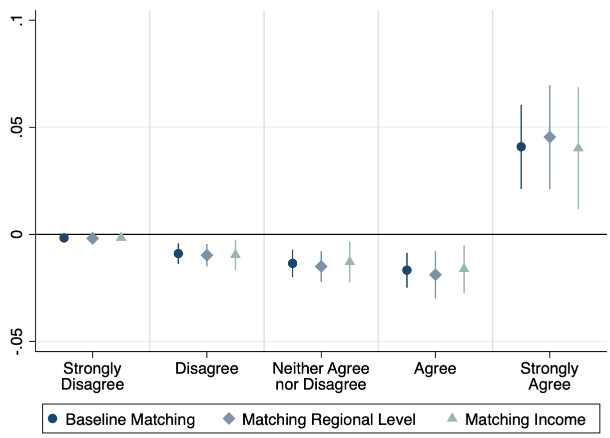
Notes: Multivariate L1 distance statistics and differences within the distribution of each variable used in the matching specification including income level. Data corresponds to our final sample, which includes working individuals aged 70 or below with information on all variables used in the baseline matching. Panel (a) corresponds to measures before matching. Panel (b) corresponds to our matched sample.

Figure D.2.: Distribution of Preferences for Redistribution: Before and After Matching with Income



Notes: Distribution of preferences for redistribution. Matching specification including income level. *"Before Matching"* represents the distribution before matching and corresponds to our final sample, which includes working individuals aged 70 or below with information on all variables used in the matching. *"After Matching"* corresponds to the distribution on the matched sample.

Figure D.3.: Average Marginal Effect of Temporary Contract on Preferences for Redistribution: Alternative Matching Specifications



Notes: Estimated average marginal effects and 95% confidence intervals corresponding to the estimation of Equation (2.1) on the three alternative matched samples using an Ordered Logit model. *"Baseline Matching"* corresponds to the results on our baseline matching specification reported in Column (6) of Table 2.2; *"Matching Regional Level"* corresponds to the results of the estimation on the matched sample including region reported in Table 2.6, Column (6), Panel (a); *"Matching Income"* corresponds to the results of the estimation on the matched sample including income level reported in Table 2.6, Column (6), Panel (b). All specifications control for political ideology, regional fixed effects, time-fixed effects, the interaction of both fixed effects, and the variables used in the matching process.

3. Decentralized Redistribution: The Impact of Tax Autonomy on Inequality

3.1. Introduction

Besides generating government revenue, personal income taxation aims to reduce income inequalities. While inequality has remained at high levels over the past decades, an important question is whether or not tax systems have reacted to this, and if so, what the efficiency costs of those policies have been. These questions become even more relevant in the presence of differences in income distribution across sub-national jurisdictions, as from an optimal tax point of view, marginal tax rates should be different across heterogeneous regions.

On theoretical grounds, the redistributive function has traditionally been attributed to central governments to minimize the efficiency trade-off associated with jurisdiction size. In a context where individuals are mobile, centralizing the tax design prevents efficiency costs derived from behavioral responses in the form of mobility across regions (Musgrave, 1959). On the other hand, the decentralization of the tax design allows regions to adapt the system based on their pre-tax income distribution, redistribution preferences, and financial needs (Milligan and Smart, 2019; Oates, 1972). While much of previous work on tax decentralization has focused on efficiency considerations, the extent to which sub-national income taxation can reduce inequality is less documented. We break new ground on this question by using tax micro-data from Spain, a country that has undertaken important efforts in decentralizing the personal income tax in recent years.

To be precise, we exploit a decentralization reform implemented in 2010, which granted substantial autonomy over half of the tax base to sub-national jurisdictions (Autonomous Communities) in Spain. Following this reform, some regions implemented more progressive tax designs with high tax rates on larger incomes, while others increased marginal tax rates for middle incomes or decreased marginal tax rates at the bottom of the income distribution. Important questions arise. Were those tax policies implemented to reduce inequality and hence adapted to the regional pre-tax distribution of income? Have these changes reduced inequality, and to what extent? And if so, what are the consequences for output and employment of those policies?

To answer these questions, we construct a tax calculator that replicates the Spanish personal income tax (PIT) for each region and year between 2008 and 2018. We apply this calculator to a stratified random sample of administrative tax records at the individual level for the same period. This calculator allows us to simulate the redistributive impact of a given tax design when applied to different pre-tax income distributions. We simulate scenarios that allow us to identify the change in inequality, measured by the regional Gini and various other inequality indices, derived from the decentralization of the tax.

This paper contributes to three different strands of the literature. First, we provide descriptive evidence about the variation in income distributions across regions. We show that heterogeneity across regions is considerable. The regional heterogeneity justifies the tax decentralization as, in this case, the optimal tax rates vary across regions (Milligan and Smart, 2019).

Second, we analyze how regional tax policies have affected the after-tax income distribution. We find that granting normative power to heterogeneous sub-national regions has decreased the average regional Gini coefficient by 0.04 points. We show that regional deviations from the central tax design lead to an increase in the Bottom 50 percent income share at expenses of a reduction in the Top 10 income share. This result implies that regional tax rates, to some extent, are endogenous to the pre-tax distribution of income.

The third objective of this paper is to analyze the potential output effects of tax policies. Given the previous results, using regional variation in tax rates might cause endogeneity issues. To overcome this problem, we apply the identification approach of Zidar (2019) to identify the causal effects of tax policies. This approach uses exogenous variation in central government tax policies, which affect regions differently because of their different pre-tax income distributions. We find that the efficiency costs of these tax shocks are relatively small. Our results parallel those of Zidar (2019) with one exception. The average wage responds to tax changes on the top 10 of the income distribution, implying important incidence effects of tax hikes on this part of the population.

A large body of literature has been analyzing the redistributive effect of tax and transfer systems. The typology of such studies found in the literature is diverse, and, in general terms, they take forms of descriptive analysis, decomposition, or simulation studies. Descriptive studies focus either on differences across countries (see for example Cantante, 2020), the evolution of redistribution for a certain group of population (Bozio et al., 2018), on the decomposition of the tax system elements' role or on the decomposition from the income point of view.[1]

Although descriptive studies are informative of the evolution and main components determining the redistributive effect of a tax system, they implicitly assume that the pre-tax income distribution change is exogenous and unrelated to tax changes (Thoresen et al., 2016). To evaluate the effects of tax policy, microsimulation tools such as the TAXISM model for the US (Feenberg and Coutts, 1993) or the EUROMOD for European countries (Sutherland and Figari, 2013) are commonly used in fixed base studies. In this body of studies, the benchmark is established by keeping the pre-tax income distribution fixed at a base year and exposing it to the tax schemes of interest.[2] While these tools allow for extended cross-country studies, they do not allow for regional simulations.

More recent studies focusing on the progressivity of the Spanish PIT evaluate welfare implications (Serrano-Puente, 2020) and the impact on fiscal revenues (Guner et al., 2020) from a macro perspective.[3] Guner et al. (2020) study how much revenue can be generated by increasing the progressivity of the personal income tax in Spain through a life-cycle model with endogenous labor supply. The two previous studies find that increasing the total tax collection is possible by increasing marginal tax rates on top earners. However, this increase has to be substantial and applied to a broad group. Serrano-Puente (2020) uses a heterogeneous household general equilibrium model to explore the relationship between fiscal policy variables and the endogenous cross-sectional distribution of income and wealth in Spain. While both studies are closely related, Serrano-Puente (2020) focuses on the welfare rather than revenue implications of an increase in the personal income tax progressivity. Their findings suggest that increasing progressivity would be optimal, even though it would involve an efficiency cost, as the optimal reform of the tax schedule would reduce wealth and income inequality at the cost of negative effects on capital, labor, and output.

[1] See Lambert (1992), Onrubia et al. (2014), and Pfähler (1990) for methodological descriptions and applications. See Shorrocks (2013) for a description and Kristjánsson (2011) and Wang et al. (2014) for adaptations and applications of the decomposition methodology.

[2] Bargain and Callan (2010) propose a decomposition to identify the effects on redistribution of the tax-benefit structure relative to changes in income levels and non-tax changes by using simulation techniques; Dardanoni and Lambert (2002) propose a transplant and compare method to establish a common base for the identification of the tax policy contribution to the change in redistribution; Lambert and Thoresen (2009) show that the "fixed" income approach may be vulnerable to base dependence, and Thoresen et al. (2012) describe a transplant and compare method which accounts for behavioral responses and apply it to the Norwegian tax reform of 2006.

[3] Previous studies have analyzed the redistributive impact of the 1990 tax reform (Castañer et al., 2004); the role of tax credits, rate structure, allowances and deductions in determining the overall progressivity (Wagstaff and Van Doorslaer, 2001); the redistributive effect of introducing the dual scheme in 2007 (Onrubia et al., 2014); or estimate parametric functions of the effective marginal tax rate (Garcıa-Miralles et al., 2019).

The existing literature provides relevant insight of the PIT characteristics and potential reforms. However, a detailed evaluation of the equity effects from a micro perspective is still missing. This study fills this gap in the literature. Section 3.2 describes in detail the tax system and reform we exploit for identification. Section 4.3 introduces the data, and Section 3.4 discusses the identification approaches. Results are discussed in Section 4.5, before the last section concludes.

3.2. Institutional Background

Spain is formed by 17 regions called Autonomous Communities which exhibit a significant level of heterogeneity in terms such as political ideology, redistribution preferences, income inequality, labor and social characteristics, financing capacity, or spending needs. Of the 17 regions, 15 follow the common tax regime and are the object of this study.[4]

The Spanish Personal Income Tax (PIT), which is characterized by its dual design, is of considerable complexity (see Garcıa-Miralles et al. (2019) for a detailed description). Income taxed by the PIT includes labor income, self-employment income, and capital income. Income is then classified based on its source into *"General Income"* and *"Capital Income"*, which is then taxed at different rates. *"Capital Income"* contains the main sources of capital income and is taxed at the same rates across regions. *"General Income"*, the focus of this study, is formed by labor income, self-employment income, and some forms of capital income. Tax brackets and marginal tax rates are set yearly by the central government, who specifies the marginal tax rates to be applied at the central and regional levels. Since 2007, regions have kept the revenues collected from applying the corresponding regional design to 33 percent of the tax base in their territory. *"General Income"* is taxed at a highly progressive scale which was common across regions before 2010 and became substantially heterogeneous across regions after the 2010 Spanish PIT reform.

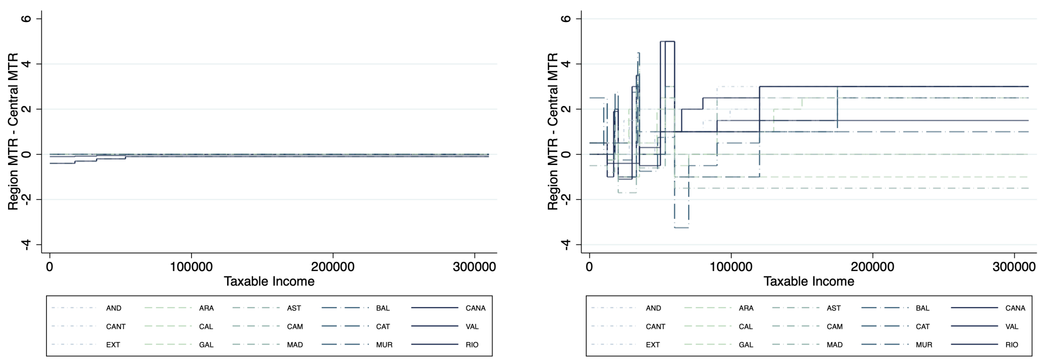
The decentralization wave that followed the Organic Law 3/2009 increased from 33 to 50 percent the share of the tax design attributed to regions, incentivizing them to make use of this newly granted regulatory power and introduce new tax brackets.[5] Before the 2010 reform, 33 percent of the PIT design was attributed to regions with normative power in tax credits and marginal tax rates. While regions could modify the marginal tax rates set at the central level, only four regions did (Figure 3.1a), and

[4]Euskadi and Navarra are not considered as they follow a historical tax system, and therefore, they are not affected by such reform.

[5]Although the reform only granted regulatory capacity for the PIT, it also increased the share of tax revenue attributed to regions from 35 to 50 percent in the case of the value-added tax, and from 40 to 58 percent in the case of special taxes.

Figure 3.1.: Regional Differences in Marginal Tax Rates

(a) Differences in 2010 (b) Differences in 2018



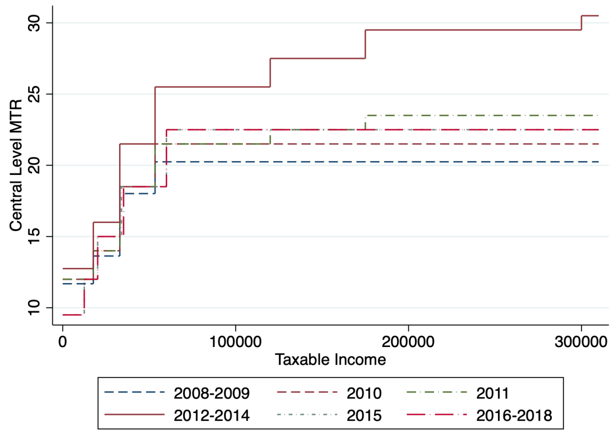
Notes: This figure depicts deviations from the central-level tax rates along the income distribution across Spanish regions in 2010 (Panel a) and 2018 (Panel b). The figures have been constructed after digitizing the regional tax books (*Libros de tributación autónomica*) published by the Spanish Ministry of Finance.

most of the normative power use was centered around tax credits.[6] Tax credits lower the effective pressure for lower-income individuals, but their redistributive capacity is limited (Díaz Caro et al., 2013). The decentralization reform extended the regional normative power to the personal and family tax-free threshold. The increase in the share of the regional tax design incentivized modifications of the tax scale. Eight years after, the degree of variation across regions induced by the PIT decentralization was substantial (Figure 3.1b).

From 2012 to 2014, the tax scale corresponding to the central government was complemented with a highly progressive scale to increase revenue and reduce the large level of public deficit. Figure 3.2 shows the evolution of general income marginal tax rates and tax brackets set by the central government. The continuous line from 2012 to 2014 corresponds to when the complementary scale was in place. Four years after the decentralization wave, the Law 26/2014 modified the PIT system again. This new regulation aimed to increase the taxpayers' disposable income by effectively reducing the tax burden. While the basic structure of the PIT design was not changed, it increased the tax base and modified the central-level tax scale by reducing the number of brackets and marginal tax rates applied to each bracket. These two shocks were equally implemented in all regions subject to the common tax regime.

[6] Before 2010, the four regions deviating from the marginal tax rate established at the central level were Valencia, Murcia, Madrid, and La Rioja. In 2009, the most significant deviations were in the regions of Madrid and La Rioja, where the marginal tax rates of the first, second, third, and fourth brackets were 0.4, 0.3, 0.2, and 0.1 percentage points lower than those established by the central government.

Figure 3.2.: Evolution of Central Level Marginal Tax Rates and Tax Brackets



Notes: This figure depicts marginal tax rates and brackets set by the central government from 2008 to 2018. The figure has been constructed after digitizing the regional tax books (*Libros de tributación autónomica*) published by the Spanish Ministry of Finance.

3.3. Data

This research draws on an individual-level stratified random sample of administrative tax records representative of the universe of Spanish taxpayers (Muestra IRPF IEF-AEAT) from 2008 to 2018. This dataset provides the information in the PIT form regarding main fillers' wage, capital income, and individual characteristics such as the number of ascendants and descendants, age, or region of residence. One limitation of this data source is the lack of information regarding individuals who are not compelled to file a tax return due to their income level. To obtain more representative inequality measures, we complement the database of main fillers with an extra database containing information such as earnings, region of residence, and age of non-tax fillers (Muestra IRPF IEF-AEAT No Declarantes).[7]

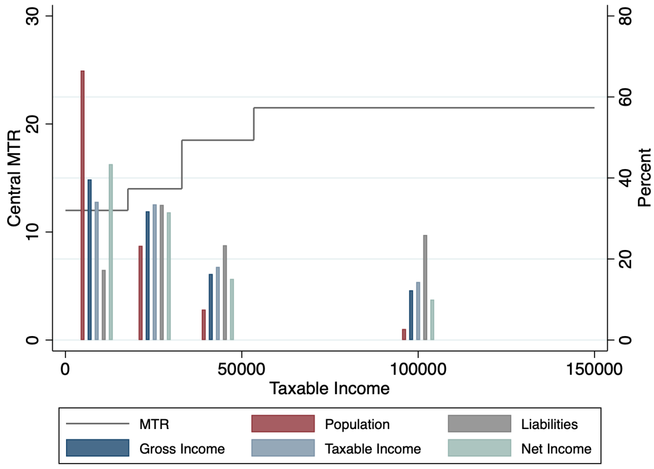
We define income at two different levels. *"General Income"* corresponds to the sum of gross income from the different income sources subject to the general tax scheme (labor income, some sources of capital income, and self-employment income).[8] *"Total Income"* adds to general income the income sources subject to the capital tax base and, therefore, is defined as all income subject to the PIT tax. The analysis is restricted to those tax fillings with a non-negative gross income. *"Liabilities"* are defined before applying tax credits. For each income level, *"Net*

[7]Individuals with labor income below 22,000 euros from a single employer are not obliged to fill up PIT taxes. The minimum threshold is reduced to 11,200 euros if an individual has multiple employers.

[8]Self-employed income and capital income are reported net of deductible expenses and tax deductions. Therefore, this measure of gross income is an under-representation of the true gross income. As Garcıa-Miralles et al. (2019) notice, this is especially relevant for self-employed income.

Income" is defined as gross income minus the corresponding liabilities.[9]

Figure 3.3.: Population, Gross Income and Taxable Income by Tax Bracket



Notes: This figure depicts the share of population, gross income, taxable income, total liabilities, and net income falling into each of the four tax brackets established at the central level in the year 2010. Income measures correspond to *"General Income"*. Gross income is defined as the sum of gross income from the different sources subject to the general tax base. The magnitudes correspond to the Muestra IRPF IEF-AEAT 2010 and include non-tax filers. The right axis shows the tax rate set by the central government to be applied at the regional level in the year 2010.

Figure 3.3 focuses on "General Income" and provides a general look at the distribution of the main variables of interest along the PIT tax base. This figure describes the share of total population, gross income, taxable income, and liabilities falling into each 2010 tax bracket.[10] Comparing the share of population and gross income falling into each of the tax brackets, this figure provides a first approximation to the degree of pre-tax income inequality. The progressive nature of the PIT design can be observed by comparing the share of gross income with the share of taxable income and liabilities in each tax bracket. Last, the redistributive effect achieved by the tax design is represented by the difference between the share of gross and net income. The heterogeneity across Spanish regions is particularly interesting for the study of the decentralization effect. As Table 3.1 shows, the patterns described by Figure 3.3 are qualitatively similar across regions, but their magnitudes are substantially different.

[9]Following the terminology of the Spanish tax system, liabilities correspond to the "cuota correspondiente a la base liquidable general" and "cuota correspondiente a la base liquidable del ahorro". In Appendix A, Tables A.1 and A.2 provide basic descriptive statistics of the main variables of interest.

[10]In the year 2010, the first tax bracket is applied to individuals with taxable income up to 17,707.20; the second tax bracket contains individuals with taxable income from 17,707.21 to 33,007.20; the third tax bracket to individuals with taxable income from 33,007.21 to 53,407.20; and the fourth tax bracket to individuals with taxable income above 53,407.20

Table 3.1.: Regional Distributions 2010. General Income.

Region	General Inc (Gini Gross)	Bracket 1		Bracket 2		Bracket 3		Bracket 4	
		Population	General Inc	Population	General Inc	Population	General Inc	Population	General Inc
AND	37.32	71.05	44.76	20.40	30.66	6.51	15.36	2.04	9.22
ARA	37.23	65.37	38.66	24.44	32.95	7.08	15.43	3.12	12.96
AST	35.51	63.30	37.76	27.70	38.38	7.05	15.68	1.95	8.18
BAL	36.35	68.04	42.09	22.08	30.18	7.29	15.91	2.59	11.82
CANAR	35.60	70.87	45.65	20.88	30.80	6.33	14.63	1.93	8.92
CANT	35.30	66.11	40.76	24.14	33.69	7.60	16.63	2.14	8.92
CLEON	35.64	69.40	44.16	22.37	32.86	6.41	14.94	1.81	8.03
CMAN	35.36	72.03	47.40	20.30	30.62	5.95	14.24	1.72	7.75
CAT	37.59	61.20	34.49	26.19	32.40	8.84	17.47	3.77	15.63
VAL	37.23	71.20	44.98	20.60	30.64	6.12	14.47	2.08	9.91
EXTR	36.61	76.98	52.39	17.12	28.70	4.44	11.81	1.45	7.10
GAL	36.46	72.29	46.74	19.83	29.88	5.98	14.31	1.90	9.06
MAD	38.48	56.18	29.26	28.58	32.63	10.84	19.68	4.39	18.43
MUR	36.17	71.93	46.64	20.28	30.86	6.09	14.59	1.70	7.91
RIO	36.40	68.39	42.63	22.46	31.97	6.87	15.37	2.28	10.03
TOTAL	37.53	66.52	39.65	23.25	31.78	7.51	16.30	2.72	12.27

Notes: This table shows basic descriptive information for each Spanish region and for Spain as a whole in year 2010. "Gini gross General Inc" is informative of the Gini index of each region. "Population" and "General Inc" indicate the share of tax fillings and general income before taxes that falls into each of the four tax brackets. The magnitudes are calculated using the Muestra IRPF IEF-AEAT of year 2010 including non-tax fillers.

Table 3.2.: Descriptive Statistics: Real Outcomes

	N	Mean	Sd	Min	Max
Ocupation Rate	180	80.95	6.45	63.78	92.83
GDP per capita	180	22,397.97	4,257.35	15,485	36,049
Labor Force Participation Rate	240	58.47	3.92	50	67
Average Wage	180	21,674.83	1,882.82	18,264.9	27,817.76

Notes: Data from the Spanish Institute of Statistics (INE). The period of time analyzed spans from 2008 to 2019 for all variables besides labor force participation which spans from 2006 to 2021.

To study the effect of tax shocks on real variables, we use data from the Spanish Institute of Statistics (INE). More specifically, we evaluate the impact of tax shocks on the regional occupation rate, labor force participation rate, GDP per capita, and average wages. The period analyzed spans from the year 2008 to the year 2019. Table 3.2 provides basic descriptive statistics of these variables.

3.4. Methodology

3.4.1. Personal Income Tax Micro Simulator

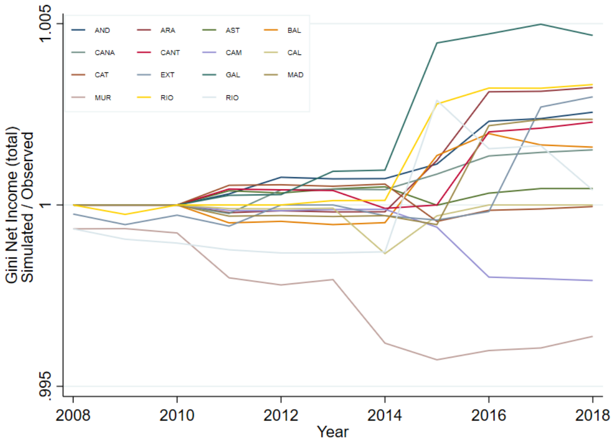
This research relies on the development of a micro-simulation tool. We develop a tax calculator that replicates the Spanish PIT design at the regional and central levels for each year from 2008 to 2018 when applied to different pre-tax income distributions. We perform our analysis by exploiting the different counterfactual scenarios generated using this simulation tool. More specifically, this instrument simulates the liabilities corresponding to the savings and general income tax base due to the central level and each region's tax design. The administrative data described above includes each taxpayer's characteristics, which we exploit to take into account tax deductions. While this microsimulation tool predicts well the tax burden derived from applying the tax schedule, we cannot account for tax credits.[11] This tax calculator allows for the simulation of multiple scenarios. Here, we focus on three of them.

PIT decentralization and its effect on redistribution. To estimate the redistributive consequences of the decentralization reform, the level of redistribution observed needs to be compared with a counterfactual scenario absent of regions' use of normative power. The tax calculator allows us to simulate, for each region, the redistributive effect that would have taken place if the region had not used its normative power and kept the marginal tax rates set at the central level. By comparing the redistributive effect achieved in this simulated counterfactual scenario to the

[11] In Appendix A, Table A.5 shows the goodness of fit of the tax calculator with the real data.

scenario where regions use their normative power, we are able to identify the change in redistribution derived from PIT decentralization. More specifically, we simulate for each individual i in region r and year t its net income $y_{i,r,t}^{s=cd}$ in the counterfactual scenario $s = cd$ where the central level tax design is applied, and its net income $y_{i,r,t}^{s=rd}$ in the scenario $s = rd$ where regions' r tax schedule is applied. We identify differences in redistribution by comparing the reduction in inequality in these two scenarios.

Figure 3.4.: Differences in Redistributive Effect from the Central Tax Design. Total Income.

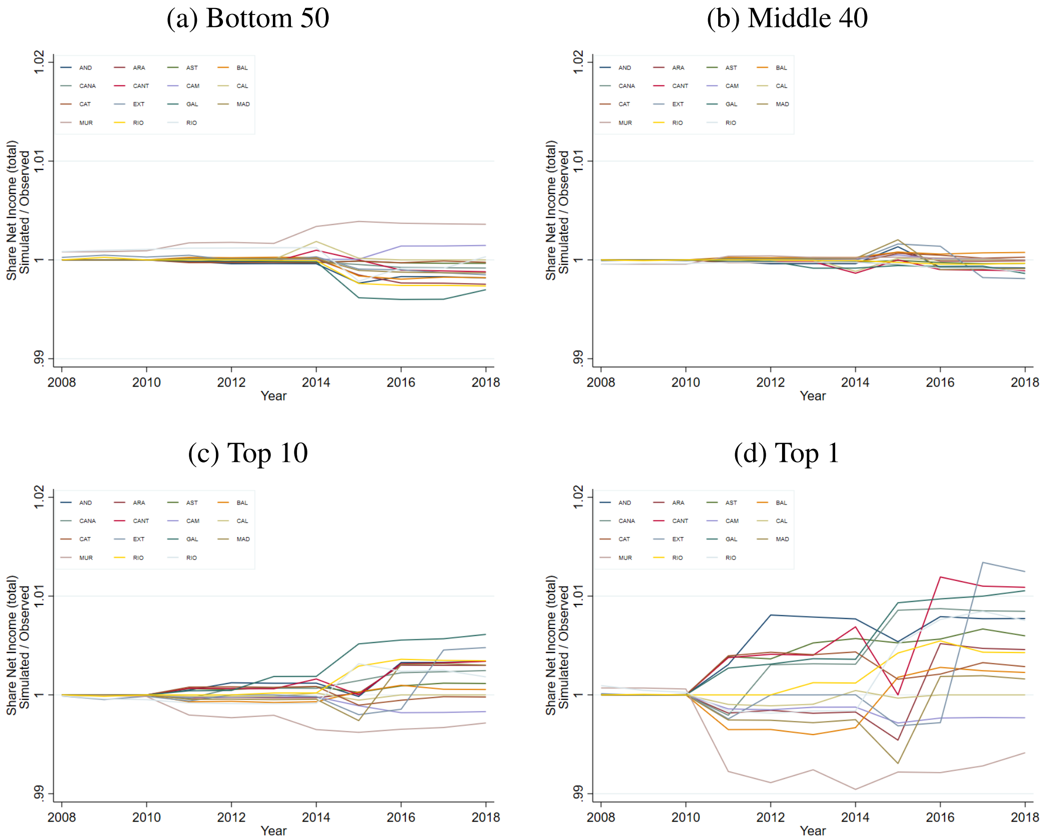


Notes: This figure shows, for each region, the evolution of the ratio between the after-tax Gini index in the counterfactual scenario where the region does not deviate from the central-level tax design and the after-tax Gini index in the observed scenario where regions use their normative power. Gini measures are relative to total income. Values larger than one imply higher inequality in the central level scenario, indicating regional deviations towards a more redistributive design.

To provide a better illustration of this exercise, Figure 3.4 reports the ratio between the after-tax Gini index in the counterfactual scenario where regions do not deviate from the central level design and the observed after-tax Gini index (i.e., the after-tax Gini index including regional deviations). Values larger than one indicate regional deviations toward a more redistributive design as correspond to cases in which the after-tax Gini index associated with the regional design is lower than under the central level design. Before 2010, differences in redistribution across regions were only present in a few cases. They became more notorious after 2010 and were magnified after 2014. Most variation was centered around zero immediately after the 2010 decentralization wave (i.e., years 2010 to 2014). However, differences became more magnified after the 2014 PIT reform, which modified the definition of taxable income and the tax scale applied at the central level.

To document differences in the use of normative power along the income distribution, Figure 3.5 replicates the previous exercise for the Bottom 50 (Panel a), Middle 40 (Panel b), Top 10 (Panel c), and Top 1 (Panel d) percent income shares. Values

Figure 3.5.: Differences in Redistributive Effect from the Central Tax Design. Total Income



Notes: This figure shows for each region and income group the evolution of the ratio between the after-tax income share in the counterfactual scenario where the region does not deviate from the central level tax design and the after-tax income share in the observed scenario where regions use their normative power. Values larger than one imply larger shares in the central level scenario than when regions use their normative power. Income measures correspond to total income (i.e., the sum of general and capital income). The bottom 50 corresponds to the group p0p50, the Middle 40 to the group p50p90, the Top 10 to the group p90p100, and the Top 1 to the group p99p100.

above one indicate a larger share of income after the central tax design rather than after the regional tax design. During the years immediately after 2010, most of the regional normative power was targeted at the upper parts of the income distribution. After 2014, deviations from the central level tax design consistently implied larger shares of income for the bottom 50 percent of the distribution (Panel a) at expenses of reductions in income shares of the top 10 percent and especially at the top 1 percent of the distribution (Panels c and d).[12]

Exclusion of behavioral responses. We isolate potential confounding effects from behavioral responses and distribution changes by keeping the pre-tax income distribution constant in 2010. More specifically, we take as a base individuals' 2010

[12]In Appendix A, Figures A.1 and A.2 show that these patterns are consistent when inequality measures and income shares only include general income.

income to simulate the yearly tax design. By performing this exercise, we exclude the possibility of changes in pre-tax income affecting our results.

Pre-tax income distribution and its effect on redistribution. We exploit the possibility of replicating different tax designs on a given pre-tax income distribution to document that the redistributive effect achieved by a given tax design is strongly influenced by the pre-tax income distribution to which it is applied. We replicate each region's tax design to the entire country's pre-tax income distribution. By keeping the pre-tax distribution constant across regions, we can compare differences in redistribution derived directly from different tax schedules.

Tax shock measures. The last exercise we perform with the tax calculator measures tax shocks derived from the central-level tax design. As described in the following sections, we apply the methodology developed by Zidar (2019) and use our tax calculator to simulate the change in tax liabilities derived from central-level tax shocks. More specifically, we compute tax shock measures by simulating the change in liabilities for each individual from the current tax schedule to the scenario where the after-shock tax schedule is applied.

3.4.2. The Effect of the PIT Decentralization on Inequality

We identify the redistributive effect of the PIT by comparing the differences between gross and net income over time. To document the impact of the tax design in reducing regional inequality, we estimate the difference between gross and net income in the scenario in which regions use their normative power and in the counterfactual scenario that mimics the tax policy of the central government for each region. We identify the effect of regional normative power by estimating the difference in net income between the observed scenario, which considers the use of regional normative power, and a counterfactual scenario in which we apply the central level design to each region. In this setting, the parallel trend assumption is mechanically satisfied as gross income is common in both scenarios.

The Gini index is one of the indices most commonly used to measure the general level of inequality in a given income distribution. We provide a first approximation to the redistributive impact achieved by the Spanish PIT system by estimating Equation (3.1) using the Gini index as an inequality measure. We measure redistribution as the reduction from the before to the after-tax Gini index. Although the Gini index serves as a measure of aggregate inequality, it does not allow to observe changes along the income distribution. To better identify the use of regions' normative power, we complement our analysis with alternative inequality measures. More specifically, we analyze variations in the share of income concentrated in the Bottom 50, Middle

40, Top 10, and Top 1 percent of the pre-tax income distribution.[13]

Baseline Specification

We break down the analysis into three periods to differentiate the decentralization effect immediately after the decentralization wave (2011 to 2014) from the impact after the 2014 PIT reform (2015 to 2018). Formally, the model we estimate is an adaptation of a triple difference model defined as follows:

$$\begin{aligned} Y_{s,l,r,t} = \ & \beta_0 + \beta_1 AT_l + \beta_2 NP_s + \beta_3 AT_l * NP_s \\ & + \beta_4 D1_t + \beta_5 AT_l * D1_t + \beta_6 NP_s * D1_t + \beta_7 NP_s * AT_l * D1_t \\ & + \beta_8 D2_t + \beta_9 AT_l * D2_t + \beta_{10} NP_s * D2_t + \beta_{11} NP_s * AT_l * D2_t \\ & + \delta X_{s,l,r,t} + \theta_r + \theta_t + \varepsilon_{s,l,r,t} \end{aligned} \tag{3.1}$$

Where the dependent variable, $Y_{s,l,r,t}$, is a given inequality measure at the income level l (before or after tax) for region r in year t under the scenario s (observed or simulated); AT_l is a dummy variable taking a value of 1 if $Y_{s,l,r,t}$ corresponds to after tax income and 0 if $Y_{s,l,r,t}$ corresponds to gross income; NP_s is a dummy variable taking a value of 1 if $Y_{s,l,r,t}$ corresponds to the observed scenario where regions use their normative power, and a value of 0 if $Y_{s,l,r,t}$ corresponds to the simulated scenario where we apply the central level tax design; $D1_t$ is a dummy variable accounting for the time period immediately after the 2010 decentralization wave and takes a value of 1 for years 2011 to 2014; $D2_t$ is a dummy variable accounting for time period after the 2014 PIT reform and takes a value of 1 for years 2015 to 2018; $X_{s,l,r,t}$ is a set of controls accounting for the share of gross income falling into each tax bracket defined as in the 2010 tax schedule; θ_r and θ_t are region and time fixed effects.

The main coefficients of interest are β_7 and β_{11}. They estimate the marginal effect derived from the use of regions' normative power in the period immediately after the decentralization reform (β_7) and the period after the 2014 PIT reform (β_{11}). To estimate the redistributive effect achieved by the central level design, β_1, β_5, and β_9 estimate the difference between gross and net income in the counterfactual scenario where all regions apply the central-level design. β_1 estimates this effect for the period before the decentralization wave, β_6 for the period from 2011 to 2014, and β_9 for the period from 2015 to 2018.

[13] The "Bottom 50" corresponds to the group p0p50, the "Middle 40" to the group p50p90, the "Top 10" to the group p90p100, and the "Top 1" to the group p99p100. In Appendix A, Table A.4 provides descriptive statistics of the main inequality measures.

Dynamic Evolution

The specification defined by Equation (3.1) allows for estimating average effects during a given period. To better identify the dynamic evolution of the effect, we adapt Equation (3.1) to an event study design which takes the following form:

$$\begin{aligned} Y_{s,l,r,t} = &\ \beta_0 + \beta_1 AT_l + \beta_2 NP_s + \beta_3 AT_l * NP_s \\ &+ \sum_{i=2008}^{i=2009} \mathbf{1}(t-0) * (\delta_{1,i} AT_l + \delta_{2,i} NP_s + \delta_{3,i} AT_l * NP_s) \\ &+ \sum_{i=2011}^{i=2018} \mathbf{1}(t-0) * (\delta_{1,i} AT_l + \delta_{2,i} NP_s + \delta_{3,i} AT_l * NP_s) \\ &+ \gamma X_{s,l,r,t} + \theta_r + \theta_t + \varepsilon_{s,l,r,t} \end{aligned} \tag{3.2}$$

In Equation (3.2), $\mathbf{1}(y = t - 0)$ are indicators for each event year relative to t=0 (2010) and the rest of the variables are defines as in Equation (3.1).

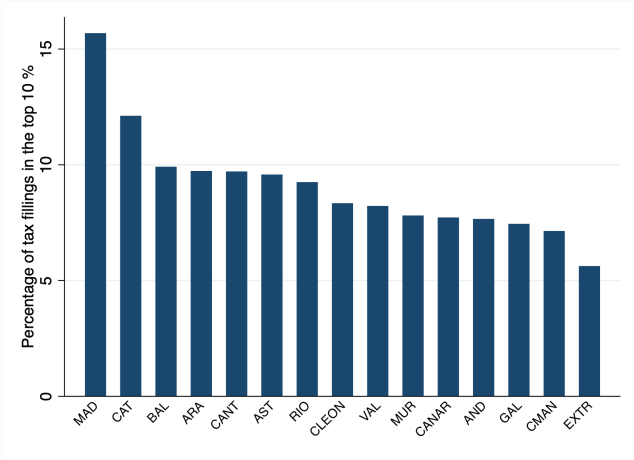
The main coefficients of interest, $\delta_{3,i}$, estimate the marginal effect from the use of regional normative power relative to the base year 2010 (β_3). $\delta_{1,i}$ estimates the redistributive effect achieved by the central level design relative to the base year 2010 (β_1). Last, $\delta_{2,i}$ estimates the redistributive effect in the scenario where regions use their normative power relative to the base year 2010 (β_2). As in the previous specification, $X_{s,l,r,t}$ controls for the gross income share of each 2010 bracket, and θ_r and θ_t account for region and time fixed effects.

3.4.3. Effects of Tax Shocks on Economic Activity, Employment, and Wages

Estimating the effect of taxation on economic activity and other outcomes is challenging as changes in taxation might be endogenous to those outcomes. To overcome this empirical challenge, we apply the methodology developed by Zidar (2019) and exploit the variation in pre-tax income distributions across regions. Figure 3.6 illustrates the percentage of each region's tax fillings falling within the top 10 percent of the national income distribution. This share widely varies across regions. The regions of Madrid and Extremadura represent the most extreme cases. While in Madrid 15 percent of tax fillings fall within the top of the national distribution, this share is 5 percent in the case of Extremadura.

To study the impact of tax shocks at the top and bottom of the income distribution on economic activity, employment, and wages, we exploit two main central-level tax changes: the introduction of the complementary scale in the year 2012 and

Figure 3.6.: Share of Tax Fillings in the Top 10 Percent of the Distribution



Notes: This figure shows the share of each region's tax fillings that fall in the top 10 percent of the national distribution of adjusted gross income. Mean value for the period 2007-2018.

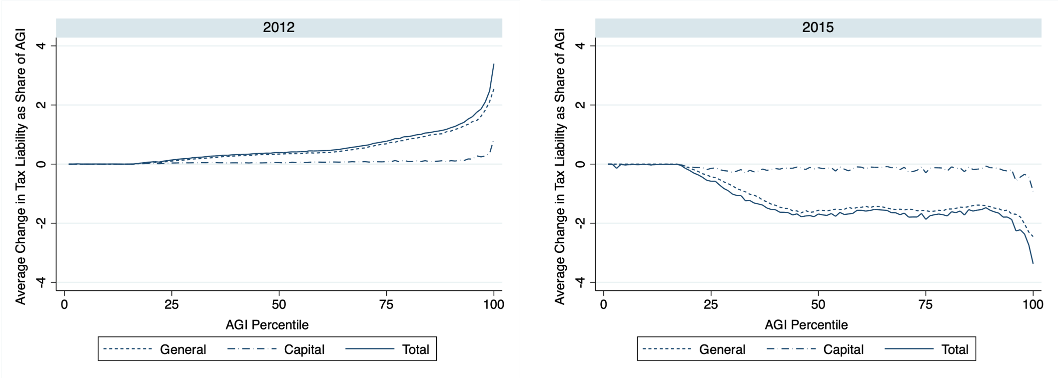
the re-definition of tax brackets and marginal tax rates in the year 2015. In 2012, the introduction of the complementary scale significantly increased tax rates along the income distribution (see Figure 3.2). In 2015, the design of the tax scale was substantially modified by the suppression of the complementary scale introduced in 2012 and by the introduction of significant differences in the definition of tax brackets and marginal tax rates. As in Zidar (2019), our identification strategy is based on the differential impact of those reforms across regions due to differences in the tax base composition.

Measure of Regional Tax Shock

The analysis of Zidar (2019) is based on the construction of tax shock measures at the year-region-income-group-level, which aggregate the individual impact of a tax shock at the region and income group level. In our setting, we compute these measures as follows. We use the tax calculator to simulate, for each individual in each region and year, the PIT liabilities the year before a tax change and their tax liability if the new tax schedule had been applied.

We compute the individual effect of each of the tax reforms by subtracting the tax liability corresponding to the current schedule (e.g., the liabilities corresponding to individual i in the year 2011 from the 2011 PIT) from the tax liability in the simulated scenario where the new tax schedule is applied (e.g., the liabilities corresponding to individual i in the year 2011 from the 2012 PIT). Figure 3.7 shows the average change in liabilities as a share of adjusted gross income for every percentile of national adjusted gross income.

Figure 3.7.: Tax Changes Over the Income Distribution



Notes: This figure depicts the average change in liabilities as a share of adjusted gross income for each percentile of national adjusted gross income. These results correspond to the tax changes of 2012 and 2015.

The year-region-income-group-level tax shock measure exploits the heterogeneity of the tax shocks illustrated in Figure 3.7 due to the differences in tax fillings falling at the top of the distribution across regions illustrated in Figure 3.6. State tax shocks are defined as the sum in mechanical changes in tax liabilities of individuals falling into a given income group over each region's GDP.[14] Income groups are then defined as the Bottom 90 and the Top 10 percent of the national distribution of adjusted gross income.

Estimation Procedure

We estimate the effect of central-level tax shocks using the direct projection approach proposed in Zidar (2019). This approach allows us to estimate the dynamic evolution of the outcome of interest before and after the tax shock takes place without imposing dynamic restrictions on its evolution. Specifically, we run a series of regressions for the time horizon periods $h \in \{-3, -2, .., 4\}$ of the following form:

$$y_{r,t+h} - y_{r,t-1} = \alpha + \beta_h^{B90} T_{r,t}^{B90} + \beta_h^{T10} T_{r,t}^{T10} + \lambda X_{r,t} + \theta_{r,h} + \theta_{t,h} + \varepsilon_{r,t,h} \tag{3.3}$$

where $y_{r,t+h} - y_{r,t-1}$ measures the change in the outcome variable y in the region r between each year t and the time horizon $t+h$; $\theta_{r,h}$ and $\theta_{t,h}$ are region and time fixed effects; and β_h^{B90} and β_h^{T10} estimate the effect associated with tax shocks at

[14]Following Zidar (2019) notation, state tax shocks are defined as $T_{r,t}^{g} = TaxLiabilityChange_{r,t}^{g}/GDP_{r,t}$ where $TaxLiabilityChange$ is the sum of mechanical changes in tax liabilities for all residents in region r, in income group g, in year t. For years in which central-level tax shocks do not take place, the measure of tax shock is set to zero.

the top 10 percent (β^{T10}) and bottom 90 percent (β^{B90}). Positive β_h^{B90} coefficients indicate a positive effect in the variation of the outcome of interest from a tax shock affecting the bottom 90 percent of the income distribution. Alternatively, positive β_h^{T10} coefficients indicate a positive effect of a tax shock affecting the top 10 percent of the income distribution.

3.5. Results

3.5.1. Impact of Tax Autonomy on Inequality

Baseline Results

Tables 3.3 and 3.4 report the estimates of the baseline model specified by Equation (3.1). Negative coefficients associated with normative power (*NP*) indicate that regions deviated from the central-level tax design to further reduce inequality in their territory. Column (1) shows the estimates before and after the PIT decentralization. Column (2) reports the results when the effect in the after-decentralization period is estimated separately for the years 2011 to 2014 (the period immediately after the decentralization wave) and the years 2015 to 2018 (the period after the suppression of the complementary scale and the redefinition of the central level tax schedule). Column (3), the preferred specification, controls for the pre-tax income share of each tax bracket and region.

By controlling for changes in the pre-tax income distribution, we ensure that our results directly identify regional responses in the form of changes in the tax design and are not biased by changes in the tax base. To isolate effects potentially driven by regions that deviated from the central-level design before 2010, we exclude them from the analysis. Column (4) excludes the region of Madrid, which shows the largest deviations from the central-level design before the decentralization wave. Last, Column (5) excludes all regions that used their normative power before the 2010 decentralization wave (i.e., Madrid, Murcia, La Rioja, and Valencia).

Results indicate that the Spanish PIT system significantly reduces inequality when measured by regional Gini indices. Results reported in Table 3.3 correspond to inequality measures of general income. Focusing on Column (3), a negative and statistically significant AT coefficient indicates that, in the pre-decentralization period, the central level PIT design would have achieved an average reduction of 4.41 points in the regional Gini index if all regions had followed its design. This magnitude corresponds to a 12 percent reduction in pre-tax inequality. After the decentralization wave, the central-level tax schedule increased its redistributive effect by 0.171 points from 2011 to 2014 ($D1 * AT$) and by 0.316 points from 2015 to 2018

Table 3.3.: Effect of Decentralization on Redistribution Measured by Changes in Gini Indices. General Income.

	(1)	(2)	(3)	(4)	(5)
AT	-4.409***	-4.409***	-4.409***	-4.355***	-4.358***
	(0.013)	(0.015)	(0.015)	(0.011)	(0.014)
AT*NP	0.006***	0.006***	0.006***	0.004***	-0
	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)
D*AT	-0.243***				
	(0.026)				
D*AT*NP	-0.0219***				
	(0.007)				
D1*AT		-0.171***	-0.171***	-0.134***	-0.126***
		(0.039)	(0.039)	(0.022)	(0.028)
D1*AT*NP		0.002	0.002	-0.003	-0.004
		(0.004)	(0.004)	(0.003)	(0.002)
D2*AT		-0.316***	-0.316***	-0.284***	-0.274***
		(0.041)	(0.041)	(0.026)	(0.035)
D2*AT*NP		-0.046***	-0.046***	-0.060***	-0.050***
		(0.010)	(0.010)	(0.008)	(0.009)
Constant	36.690***	36.690***	36.630***	36.390***	36.300***
	(0.034)	(0.033)	(0.085)	(0.118)	(0.122)
Observations	2,640	2,640	2,640	2,464	1,936
R-squared	0.967	0.967	0.967	0.972	0.970
RFE	Yes	Yes	Yes	Yes	Yes
TFE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
Excluded Observations	No	No	No	MAD	VAL MUR RIO MAD

Results from estimating Equation (3.1). Inequality is measured by the regional Gini Index of general income. Controls include the share of gross income subject to the general tax rate falling into each tax bracket. Tax brackets are defined based on the 2010 tax schedule. AT is a dummy taking a value of one if the inequality measure corresponds to after-tax income and zero if it corresponds to pre-tax income. NP is a dummy taking a value of one if the inequality measure corresponds to the scenario where regions use their normative power and zero if regions follow the central-level tax design. D is a dummy variable taking a value of one for the after-decentralization period. $D1$ is a dummy variable taking a value of one for the period immediately after the 2010 decentralization (2011 to 2014). $D2$ is a dummy variable taking a value of one for the period after the 2014 PIT reform (2015 to 2018). Standard errors clustered at the region-year level and bracket-year-income level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$(D2 * AT)$.

The marginal effect from the use of regions' normative capacity is estimated by $AT * NP$. As shown in the second row, the regions that deviated from the central-level design before the decentralization reform used their normative capacity to move toward less redistributive designs. From 2011 to 2014, once regions started using their newly granted normative power, $D1 * AT * NP$ indicates that regional inequality was not affected by the use of regional normative capacity. Nevertheless, after the 2014 PIT reform, regional deviations from the central-level design increased

Table 3.4.: Effect of Decentralization on Redistribution Measured by Changes in Gini Indices. Total Income.

	(1)	(2)	(3)	(4)	(5)
AT	-4.250***	-4.250***	-4.250***	-4.208***	-4.214***
	(0.010)	(0.013)	(0.012)	(0.006)	(0.008)
AT*NP	0.005***	0.005***	0.005***	0.003***	0
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
D*AT	-0.310***				
	(0.016)				
D*AT*NP	-0.019***				
	(0.006)				
D1*AT		-0.264***	-0.264***	-0.228***	-0.215***
		(0.027)	(0.027)	(0.007)	(0.014)
D1*AT*NP		0.002	0.002	-0.003	-0.004*
		(0.004)	(0.004)	(0.006)	(0.002)
D2*AT		-0.355***	-0.355***	-0.329***	-0.312***
		(0.019)	(0.018)	(0.010)	(0.012)
D2*AT*NP		-0.040***	-0.040***	-0.052***	-0.043***
		(0.011)	(0.011)	(0.007)	(0.008)
Constant	38.140***	38.140***	38.000***	37.650***	37.530***
	(0.045)	(0.045)	(0.134)	(0.146)	(0.147)
Observations	2,640	2,640	2,640	2,464	1,936
R-squared	0.944	0.944	0.944	0.946	0.949
RFE	Yes	Yes	Yes	Yes	Yes
TFE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes
Excluded Observations	No	No	No	MAD	VAL MUR RIO MAD

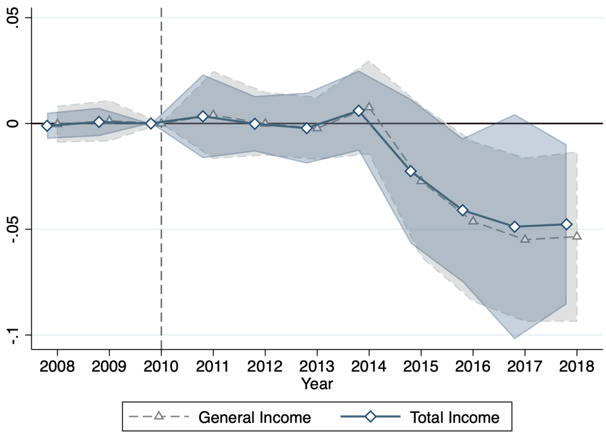
Results from estimating Equation (3.1). Inequality is measured by the regional Gini Index of total income. Controls include the share of gross income subject to the general tax rate falling into each tax bracket. Tax brackets are defined based on the 2010 tax schedule. AT is a dummy taking a value of one if the inequality measure corresponds to after-tax income and zero if it corresponds to pre-tax income. NP is a dummy taking a value of one if the inequality measure corresponds to the scenario where regions use their normative power and zero if regions follow the central-level tax design. D is a dummy variable taking a value of one for the after-decentralization period. $D1$ is a dummy variable taking a value of one for the period immediately after the 2010 decentralization (2011 to 2014). $D2$ is a dummy variable taking a value of one for the period after the 2014 PIT reform (2015 to 2018). Standard errors clustered at the region-year level and bracket-year-income level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the redistributive effect of the tax ($D2 * AT * NP$). In Column (3), the additional reduction in the Gini index achieved by the regional tax design (0.046) indicates that, on average, regions use their normative power to move toward tax schedules achieving a larger reduction of regional inequality.

In Table 3.4, we show that the results are consistent when including capital income to measure inequality. The higher concentration of capital income in the upper parts of the distribution implies an increase in the pre-tax Gini index before the decentralization wave from 36.6 to 38. Focusing on Column (3), a negative and statistically significant AT coefficient indicates that, in the pre-decentralization period, the central level tax design achieved a 4.25 point reduction in regional inequality, representing an 11 percent reduction in the Gini index. From 2011 to 2014, the central-level tax design reduced regional inequality by 0.264 additional points ($D1 * AT$). This reduction is further increased to 0.355 percentage points from 2015 to 2018 ($D2 * AT$). Focusing on the use of regions' normative power, $D1 * AT * NP$ indicates that, from 2011 to 2014, regional deviations from the central-level tax schedule did not lead to further reductions in regional inequality. Yet, from 2015 to 2018 regions used their normative power to further reduce regional income inequality by an average of 0.052 percentage points ($D2 * AT * NP$).

Columns (4) and (5) of Tables 3.3 and 3.4 replicate the same regressions excluding Madrid (Column 4) and Valencia, Murcia, La Rioja, and Madrid (Column 5). While the results are stable, two coefficients are worth commenting. First, the marginal effect of normative power in the pre-decentralization period, $AT * NP$, equals zero. This result indicates that, before the decentralization wave, the rest of the regions followed the same design as the one established at the central level. Second, the decentralization effect in the 2011-2014 period ($D1 * AT * NP$) is now negative, although not statistically significant. These results indicate that including these four regions partially drives the results in Column (3).

Figure 3.8.: Dynamic Results: Effect of Decentralization on Redistribution Measured by Changes in Gini Indices



Notes: Results correspond to the estimation of Equation (3.2). Inequality is measured by regional Gini Indices. The estimated coefficients represent the marginal change in redistribution derived from regions' normative power relative to 2010. Triangular coefficients correspond to inequality measures of income subject to the general tax base. Coefficients represented by a rhombus correspond to inequality measures of general and capital income. Negative coefficients indicate a larger reduction in the after-tax Gini index than the reduction achieved without regional normative power. Coefficients estimated while controlling by each bracket income share, regional and time fixed effects. Standard errors clustered at the region-year level and bracket-year-income level. Confidence intervals at 95 percent.

We estimate Equation (3.2) to study the temporal evolution of the use of regional normative power. Figure 3.8 shows the yearly marginal change in redistribution achieved by the use of regions' normative capacity relative to the year 2010. Negative coefficients indicate a larger reduction in the after-tax Gini index relative to the counterfactual scenario where the tax schedule is set by the central government. Coefficients represented by a rhombus report the results when inequality measures include general and capital income. Coefficients represented by a triangle report the results when inequality measures include only general income. As suggested above, during the years following the decentralization reform regional deviations where centered around zero and did not significantly reduce regional inequality. Nevertheless, after 2014, regional deviations achieved larger levels of redistribution. These results further demonstrate that the use of regions' normative power reduces inequality in similar magnitudes regardless of the inclusion of capital income.[15]

Other Inequality Measures

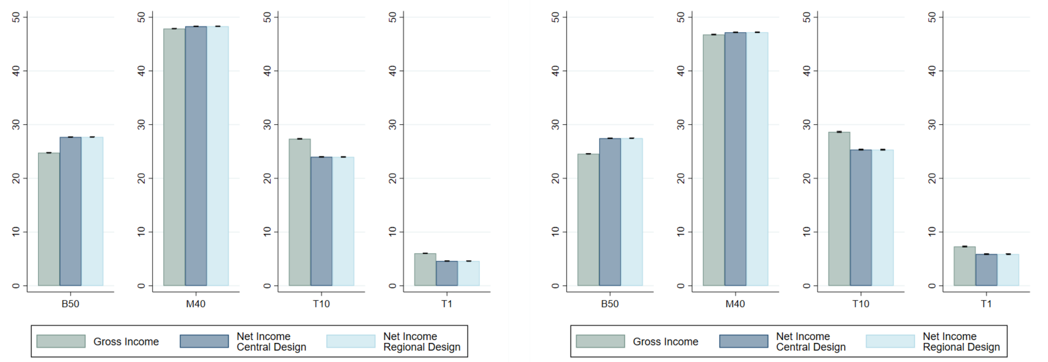
We replicate the previous analysis to different inequality measures. Figure 3.9 illustrates the impact of the PIT at the different parts of the income distribution. This figure reports the results from estimating Equation (3.1) for the after-decentralization period. *"Gross Income"* represents the share of pre-tax income accumulated by the Bottom 50, Middle 40, Top 10, and Top 1 percent of the income distribution. *"Central Design"* represents the share of after-tax income accumulated by each part of the income distribution in the scenario where regions follow the central-level tax design. *"Regional Desing"* represents the share of after-tax income accumulated by each part of the income distribution in the scenario where regions use their normative power. The magnitudes correspond to the average effect after the 2010 decentralization. These results indicate that the PIT tax schedule significantly affects the share of income at the two extremes of the distribution. In both scenarios, the PIT increases the Bottom 50 income share and decreases the share of income at the Top 10 and Top 1 percent of the distribution. The PIT does significantly affect the Middle 40 income share.

The results reported in Table 3.5 offer a closer look at the redistributive effect of the PIT design. This table reports the results of estimating Equation (3.1) for the Bottom 50, Middle 40, Top 10, and Top 1 percent income shares. Panel (a) shows the results when the analysis only considers income subject to the general tax base. Panel (b) shows the results when the analysis includes capital income. As Figure 3.9

[15]In Appendix B we provide further results derived from the estimation of Equation (3.2). Figure B.1 reports the dynamic effect of regions' redistributive effect when excluding regions deviating from the central-level tax design before the 2010 decentralization wave. Figure B.2 displays the $\delta_{i,1}$ coefficients which estimate the redistributive effect achieved by the central-level tax design relative to 2010. In Appendix E, Table E.1 replicates the analysis using inequality measures at the national level. Results show that regional normative power did not impact national-level inequality.

Figure 3.9.: Before and After Tax Income Shares

(a) General Income (b) Total Income



Notes: Results from estimating Equation (3.1) when the dependent variable is the share of income of the Bottom 50, Middle 40, Top 10, and Top 1 percent of the income distribution. Results correspond to the after-decentralization period. Shares of income measured at the regional level. Panel (a) corresponds to measures of income subject to the general tax base. Panel (b) corresponds to measures including capital income. Controls include the share of gross income corresponding to the general tax base falling into each tax bracket. Tax brackets are defined based on the 2010 tax schedule. Standard errors clustered at the region-year level and bracket-year-income level.

advanced, the central level design substantially affects the Bottom 50 and Top 10 percent income shares. Focusing on income subject to the general tax base (Panel a), before the decentralization wave (AT), the central-level tax schedule increased the Bottom 50 income share by 11 percent and decreased the income share of the Top 10 percent by 11.7 percent.

The magnitude of the effect is slightly reduced when the analysis considers capital income (Panel b). In this case, the central-level design increases by 10.8 percent the Bottom 50 percent income share and decreases by 10.7 percent the Top 10 percent income share. The effect for the Middle 40 is small. The central level tax schedule increases by 0.9 percent and 0.8 percent the share of income accumulated in this part of the distribution. Consistent with the redistributive nature of the tax design, the largest reduction in income takes place in the Top 1 percent. Applying the central-level tax design reduces its share of general income by 22.4 percent (Panel a) and its share of total income by 17.2 percent (Panel b). The smaller effect for total income than general income is due to the substantial share of capital income accumulated at the top of the distribution.

Table 3.5.: Effect of Decentralization on Redistribution Measured by Changes in Income Shares

	(a) General Income				(b) Total Income			
	B50	M40	T10	T1	B50	M40	T10	T1
AT	2.733***	0.459***	-3.192***	-1.341***	2.671***	0.383***	-3.054***	-1.238***
	(0.007)	(0.006)	(0.006)	(0.028)	(0.005)	(0.008)	(0.013)	(0.011)
AT*NP	-0.005***	0.002***	0.002*	0.000	-0.004***	0.003***	0.001***	-0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
D1*AT	0.138***	-0.022	-0.116**	-0.055	0.187***	0.0307*	-0.217***	-0.147***
	(0.014)	(0.028)	(0.039)	(0.053)	(0.009)	(0.017)	(0.030)	(0.023)
D1*AT*NP	-0.002	0.002	-0.000	0.002	-0.002	0.002	-0.000	0.002
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
D2*AT	0.250***	-0.037	-0.213***	-0.124**	0.258***	0.022**	-0.280***	-0.201***
	(0.015)	(0.028)	(0.049)	(0.053)	(0.006)	(0.010)	(0.019)	(0.016)
D2*AT*NP	0.030***	0.009	-0.039***	-0.023***	0.027***	0.006	-0.033***	-0.018***
	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)	(0.007)	(0.010)	(0.006)
Constant	24.800***	47.930***	27.280***	5.999***	24.630***	46.880***	28.490***	7.183***
	(0.047)	(0.057)	(0.085)	(0.077)	(0.061)	(0.112)	(0.155)	(0.162)
Observations	2,640	2,640	2,640	2,640	2,640	2,640	2,640	2,640
R-squared	0.966	0.944	0.961	0.952	0.960	0.907	0.923	0.885
RFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded Observations	No	No	No	No	No	No	No	No

Notes: Results from estimating Equation (3.1). Inequality is measured by the income shares of the Bottom 50, Middle 40, Top 10, and Top 1 percent of the income distribution. Panel (a) reports measures of income subject to the general tax base. Panel (b) includes capital income in the analysis. Income shares defined at the regional level. Controls include the share of gross income subject to the general tax rate falling into each tax bracket as defined in 2010 tax schedule. *AT* is a dummy taking a value of one if the inequality measure corresponds to after-tax income and zero if it corresponds to pre-tax income. *NP* is a dummy taking a value of one if the inequality measure corresponds to the scenario where regions use their normative power and zero if regions follow the central-level tax design. *D* is a dummy variable taking a value of one for the after-decentralization period. $D1$ is a dummy variable taking a value of one for the period immediately after the 2010 decentralization (2011 to 2014). $D2$ is a dummy variable taking a value of one for the period after the 2014 PIT reform (2015 to 2018). Standard errors clustered at the region-year level and bracket-year-income level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

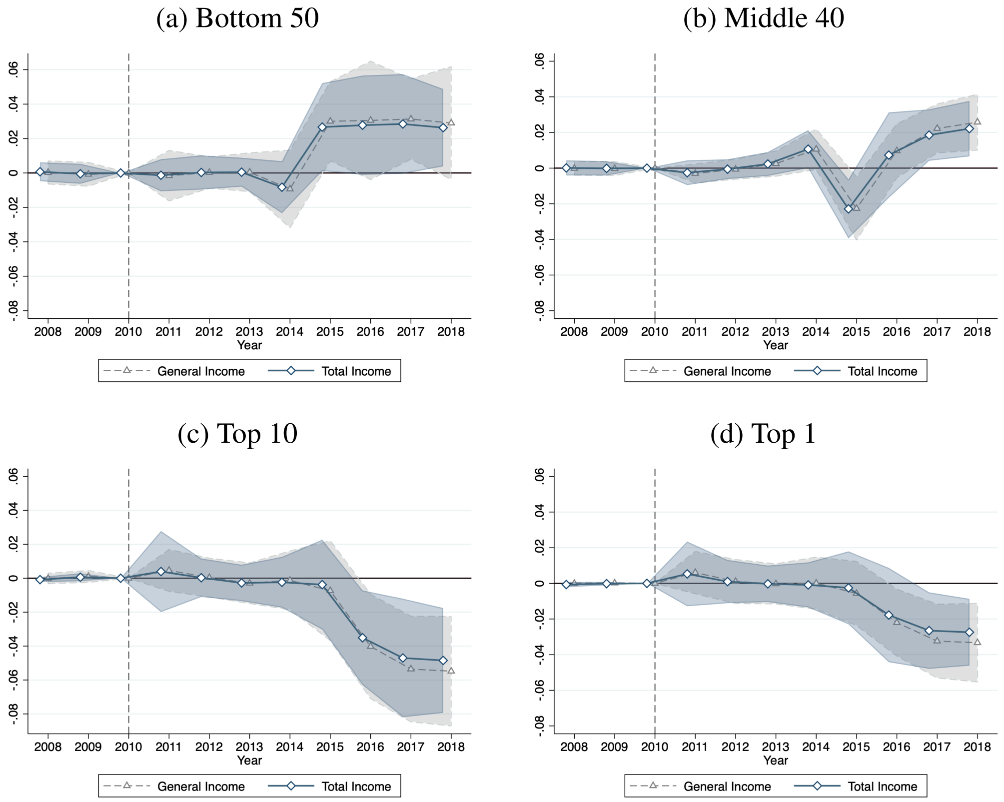
In Table 3.5, $D1*AT$ and $D2*AT$ represent the average change in income shares of each group due to changes in the central-level tax design. In Panel (a), $D1*AT$ indicates that, from 2011 to 2014, the central-level tax design further increased the share of general income accumulated by the Bottom 50 and reduced the Top 10 percent income share. The coefficients $D2*AT$ indicate that, from 2015 to 2018, the central-level tax design further increased its redistributive effect. During this period of time the central-level design further increased the Bottom 50 income share and reduced the income shares of the Top 10 and, especially, the Top 1 percent.

The average marginal change in income shares due to the use of regions normative power is estimated by $AT*NP$, $D1*AT*NP$, and $D2*AT*NP$. Consistent with the previous results, before 2010, the regions that deviated from the central-level tax design used their normative capacity to reduce the redistributive effect of their tax design. Coefficients estimated by $AT*NP$ show that during the pre-decentralization period, regions deviated toward tax designs leading to a slightly lower increase in the Bottom 50, a larger increase in the Middle 40, and a slightly lower decrease in the Top 10 and Top 1 income shares. During the period from 2011 to 2014, this effect disappears ($D1*AT*NP$), and it is reversed during the period from 2015 to 2018 ($D2*AT*NP$).[16] The estimated $D2*AT*NP$ coefficients indicate that after 2014 regions used their normative power to deviate toward slightly more redistributive tax designs. Although the Middle 40 income share is not affected by regional deviations from the central level tax design, regions use their normative power to move toward designs further increasing the Bottom 50 income share at expenses of the Top 10, and, more specifically, the Top 1 income shares. This effect is consistent whether income shares correspond to general income (Panel a) or include capital income (Panel b).[17]

[16]In Appendix B, Table B.1 reports the results when we exclude from the analysis regions which deviated from the central level tax design before 2010. In this case, from 2011 to 2014, the use of regional normative power increased the Middle 40 income share and decreases the Top 10 and Top 1 percent income shares.

[17]In Appendix E, Table E.2 shows the effect for national income shares. From 2011 to 2014, regional deviations from the central tax design slightly decreased the Middle 40 income share and increased the Top 10 and Top 1 income shares. This effect disappears after 2014. From 2015 to 2018, regional deviations from the central-level tax design led to an increase in the Bottom 50 income share without significantly affecting the rest of the income distribution.

Figure 3.10.: Dynamic Results: Effect of Decentralization on Redistribution Measured by Changes in Income Shares



Results from estimating Equation (3.2) when the dependent variables are the Bottom 50, Middle 40, Top 10, and Top 1 percent income shares. Inequality measures are computed at the regional level. The estimated coefficients represent the marginal change in income shares derived from the use of regions' normative power relative to 2010. Triangular coefficients correspond to income shares of income subject to the general tax base. Coefficients represented by a rhombus correspond to income shares of general and capital income. Controls include the share of gross income corresponding to the general tax base falling into each tax bracket as defined by the 2010 tax schedule. Standard errors are clustered at the region-year level and bracket-year-income level.

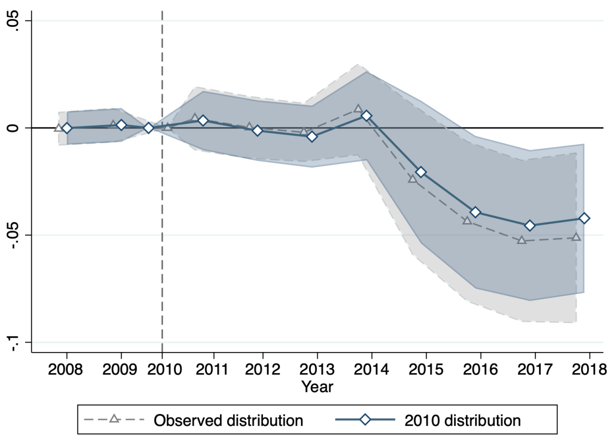
Figure 3.10 illustrates the temporal evolution of the decentralization effect relative to 2010. This effect is estimated by the δ_3 coefficients in Equation (3.2). As advanced by the results in Table 3.5, before 2014, regional deviations from the central level tax design were centered around zero and did not affect the average regional redistributive effect of the tax design. After 2015, regions moved toward designs increasing the Bottom 50 income share and reducing the Top 10 income share. In the case of the Middle 40, it was after 2016 that regions started deviating toward designs increasing its income share.

Exclusion of Behavioral Responses

The redistributive effect achieved by a tax mainly depends on two factors: the progressivity of tax design and the pre-tax income distribution to which such design is applied. Thus, the results reported in the previous section can be altered by behavioral responses to the tax reform and exogenous changes in the pre-tax income distribution consequence of the 2008 economic and financial crisis. To isolate such effects, we include in our analysis a scenario in which we keep the pre-tax income distribution constant in 2010.

By applying each year's tax design to the 2010 pre-tax income distribution, we are able to measure the redistributive effect in a counterfactual scenario absent of changes in the income distribution (i.e., without behavioral responses). Including this extra counterfactual scenario allows, on the one hand, to isolate the effect derived from potential behavioral responses and, on the other, to identify the change in redistribution derived from differences in pre-tax distributions over time. Two relevant results derive from this analysis. First, distributional changes do not significantly affect the decentralization effect reported in the previous section (Figure 3.11). Second, changes in the pre-tax income distribution enhanced the redistributive effect of the tax design (Figure 3.12).

Figure 3.11.: Effect of Decentralization on Redistribution Measured by Changes in Gini Indices. Total Income.



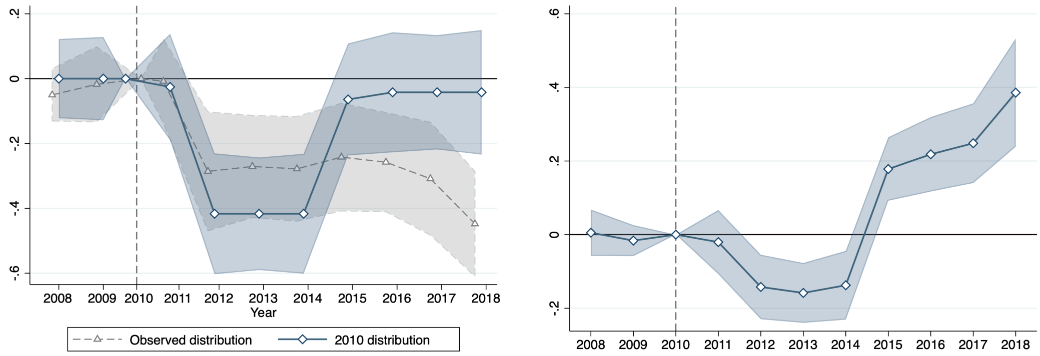
Notes: Results correspond to the estimation of Equation (3.2) adapted to include the counterfactual scenario where we keep the pre-tax income distribution constant at the year 2010. Inequality is measured by the regional Gini Index. Gini indices include both general and capital income. Coefficients represent the marginal change in redistribution derived from regions' normative power relative to 2010. Negative coefficients indicate a larger reduction in the after-tax Gini index relative to the reduction achieved without the use of regional normative power. Coefficients represented by a rhombus correspond to the scenario where the pre-tax income distribution is fixed in 2010. Triangular coefficients correspond to the scenario where the yearly pre-tax income distribution is observed. Coefficients estimated while controlling by each bracket income share, regional and time fixed effects. Standard errors clustered at the region-year level and bracket-year-income level. Confidence intervals at the 95 percent.

Figure 3.11 reports the average effect on regional redistribution due to the PIT decentralization. These results correspond to the estimation of Equation (3.2) adapted to include the extra counterfactual scenario in which we keep each region's pre-tax distribution constant in 2010. Triangular coefficients correspond to the scenario where we apply the tax schedule to the observed pre-tax income distribution. Coefficients represented by a rhombus correspond to the scenario in which we keep the pre-tax income distribution constant in 2010. These results corroborate that the increase in redistribution derived from the use of regions' normative power is not driven by pre-tax distribution changes.[18]

Figure 3.12.: Central Level Redistributive Effect

(a) Redistributive Effect of the Central Level Tax Design. Total Income.

(b) Marginal Effect of Changes in Income Distribution. Total Income.



Notes: Results corresponding to the estimation of Equation (3.2) adapted to include the counterfactual scenario where we keep the pre-tax income distribution constant in 2010. Inequality is measured by the regional Gini Index. Gini indices take into account both general and capital income. Panel (a) represents the redistributive effect achieved by the central-level tax design. Triangular coefficients correspond to the scenario in which the tax design is applied to each year's pre-tax income distribution. Coefficients represented by a rhombus correspond to the scenario where the pre-tax income distribution is kept constant in 2010. Negative coefficients indicate reductions in the Gini index due to the application of tax design. Panel (b) reports the marginal change in the redistributive effect of the central-level tax design due to changes in the pre-tax distribution relative to 2010. Positive coefficients indicate a larger redistributive effect under the corresponding pre-tax distribution rather than the one of the year 2010. Coefficients estimated while controlling by each bracket income share, regional and time fixed effects. Standard errors clustered at the region-year level and bracket-year-income level. Confidence intervals at the 95 percent.

Figure 3.12 illustrates the effect of changes in the pre-tax income distribution on the redistributive effect achieved by the central-level tax design. Results of Panel (a) represent the redistributive effect achieved by the central-level tax in the scenario where we apply the tax schedule to each year's observed pre-tax income distribution (triangular coefficients) and in the counterfactual scenario where we keep the pre-tax distribution constant in 2010 (rhomboidal coefficients). These results show that changes in the pre-tax income distribution substantially affect the redistributive effect achieved by the tax design. Coefficients reported in Panel (b) represent the marginal effect of changes in the pre-tax income distribution on redistribution. Positive coefficients indicate a larger reduction in inequality due to differences in the pre-tax distribution relative to 2010. From 2012 to 2014, changes in the pre-tax distribution implied a lower redistributive effect of the tax design.

[18] In Appendix C, Figure C.1 replicates the analysis for the Bottom 50, Middle 40, Top 10, and Top 1 percent income shares. The results from this analysis corroborate that our baseline results are not affected by behavioral responses or exogenous changes in the pre-tax income distribution.

After 2014, the evolution of the pre-tax distribution helped achieve larger inequality reductions.[19]

3.5.2. Pre-tax Income Inequality and its Effect on Redistribution

In this section, we document that the redistributive effect achieved by a given tax design is strongly affected by the pre-tax income distribution to which such design is applied. To perform this exercise, we use the tax calculator to simulate the redistributive effect of each region's tax schedule when applied to a fixed pre-tax income distribution. By keeping the distribution constant, we are able to observe the differences in redistribution derived directly from tax schedule variations. We then compare the redistributive effect observed in this counterfactual scenario to the one achieved by each region's tax schedule when applied to its regional pre-tax income distribution. The difference between these two scenarios illustrates how the pre-tax income distribution affects the level of redistribution achieved by a given tax design.

Table 3.6 summarizes the results of this exercise.[20] To avoid confounding effects derived from heterogeneous accumulations of capital income along the income distribution, Panel (a) only considers income subject to the general tax base. Panel (a.i) shows the reduction in inequality achieved by each region's tax schedule when applied to the whole country's income distribution. In this scenario, where the pre-tax income distribution is constant across regions, we can compare the redistributive capacity of the different tax schedules. The most significant reduction in inequality is achieved by Extremadura which reduced the Gini index by 14.54 percent. At the end of the ranking, Madrid's tax design reduces the Gini Index by 13.50 percent.

Panel (a.ii) shows the reduction in inequality achieved by each region's tax schedule when applied to its income distribution. In this panel, different redistributive effects are due to differences in pre-tax income distributions and tax schedules. Comparisons between Panel (i) and Panel (ii) indicate that the pre-tax income distribution to which a tax schedule is applied is an important factor determining its redistributive effect. Focusing on the ranking positions of Extremadura, the region with the tax schedule with the largest redistributive capacity, the redistributive effect of its tax design falls from the 1st to the 15th position when we consider its regional pre-tax income distribution. On the contrary, focusing on Madrid, the region with the tax schedule with the lowest redistributive capacity, it jumps from the last to second

[19] In Appendix C, Figure C.2 replicates this analysis for the Bottom 50, Middle 40, Top 10, and Top 1 percent income shares. Results show that the increase in redistribution due to distribution changes is mainly driven by an increase in the Bottom 50 and a decrease in the Top 10 percent income shares.

[20] These simulations are performed using the tax schedules and pre-tax income distributions of 2018, the last year of our data.

position when considering its pre-tax income distribution.

Table 3.6.: Tax Schedule Redistributive Effect on Different Pre-Tax Income Distributions

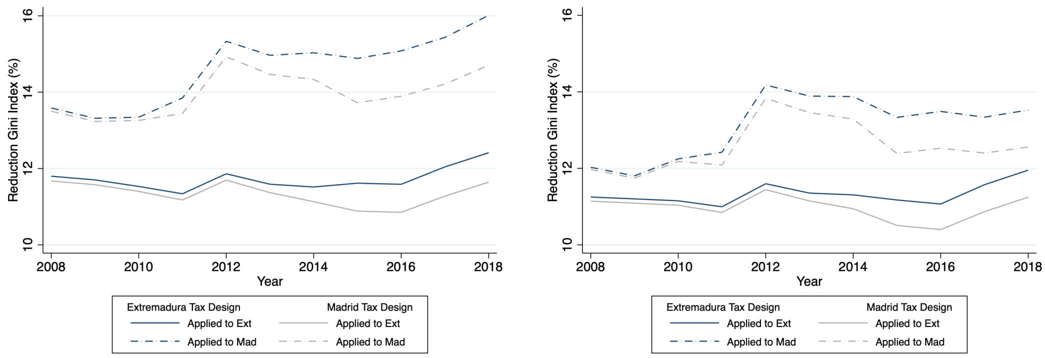
(a) General Income								
	(i) Full country distribution				(ii) Regional Distribution			
REGION	Top Bracket Taxable Income (%)	Gini Gross Income	Gini Reduction (%)	Ranking (Reduction)	Top Bracket Taxable Income (%)	Gini Gross Income	Gini Reduction (%)	Ranking (Reduction)
EXTR	17.29	37.92	14.54	1	9.23	36.75	12.41	15
VAL	17.29	37.92	14.28	2	14.74	37.29	13.73	6
ARA	17.29	37.92	14.28	3	12.95	35.04	13.55	7
MUR	17.29	37.92	14.26	4	12.25	36.49	13.17	10
AND	17.29	37.92	14.26	5	12.19	37.69	12.71	11
CANT	17.29	37.92	14.23	6	13.08	35.54	13.40	9
GAL	17.29	37.92	14.13	7	12.76	35.83	13.78	5
BAL	17.29	37.92	14.10	8	19.58	36.34	15.40	1
CANAR	17.29	37.92	14.07	9	14.16	36.38	14.05	4
AST	17.29	37.92	14.06	10	10.47	34.76	12.52	14
RIO	17.29	37.92	14.02	11	13.41	35.15	13.52	8
CAT	17.29	37.92	13.96	12	19.32	37.09	14.48	3
CMAN	17.29	37.92	13.88	13	9.88	34.91	12.62	13
CLEON	17.29	37.92	13.65	14	11.02	35.14	12.68	12
MAD	17.29	37.92	13.50	15	27.83	40.98	14.70	2
(b) Total Income								
	(i) Full country distribution				(ii) Regional Distribution			
REGION	Top Bracket Taxable Income (%)	Gini Gross Income	Gini Reduction (%)	Ranking (Reduction)	Top Bracket Taxable Income (%)	Gini Gross Income	Gini Reduction (%)	Ranking (Reduction)
EXTR	18.44	40.42	13.20	1	9.38	37.74	11.95	13
VAL	18.44	40.42	12.98	2	15.74	39.67	12.63	5
ARA	18.44	40.42	12.97	3	13.61	36.99	12.46	7
AND	18.44	40.42	12.96	4	12.76	39.21	11.99	12
MUR	18.44	40.42	12.96	5	13.15	38.34	12.38	8
CANT	18.44	40.42	12.94	6	13.85	37.65	12.23	9
GAL	18.44	40.42	12.86	7	13.94	37.90	12.79	3
BAL	18.44	40.42	12.82	8	21.70	41.44	12.78	4
CANAR	18.44	40.42	12.81	9	14.71	38.15	13.15	1
AST	18.44	40.42	12.80	10	11.01	36.39	11.71	15
RIO	18.44	40.42	12.78	11	14.54	37.87	12.13	10
CAT	18.44	40.42	12.69	12	20.71	39.87	12.99	2
CMAN	18.44	40.42	12.65	13	10.04	35.94	12.07	11
CLEON	18.44	40.42	12.46	14	11.51	36.67	11.91	14
MAD	18.44	40.42	12.34	15	29.23	44.71	12.56	6

This table illustrates the reduction in income inequality achieved by a given tax schedule when applied to different pre-tax income distributions. Panel (a) only considers income subject to the general tax base. Panel (b) includes capital income. Panel (a.i) and Panel (b.i) show the reduction of Gini indices when each region's tax schedule is applied to the entire country's pre-tax income distribution. Panel (a.ii) and Panel (b.ii) show the reduction in the Gini indices when each region's tax design is applied to its pre-tax income distribution. Pre-tax income distributions and tax schedules correspond to the year 2018. Positions in the ranking are assigned based on the reduction of the Gini index in each scenario. Higher positions in the ranking correspond to regions with larger inequality reductions. Top Bracket Taxable income indicates the percentage of taxable income falling into the top tax bracket defined in the 2010 tax schedule.

Panel (b) includes capital income in the analysis. Panel (b.i) shows the redistributive effect of each region's tax design when applied to the entire country's pre-tax income distribution. Two main observations derive from this analysis. First, the inclusion of capital income does not alter the ranking. Second, including capital income in the analysis decreases the reduction in inequality achieved by the tax design. Although including capital income increases the gross income Gini index from 37.92 to 40.42, the percentage reduction in inequality is lower in this scenario. In this case, the tax design of Extremadura reduces the Gini index by 13.20 percent. In the case of Madrid, the Gini index is reduced by 12.34 percent. Panel (b.ii) shows the inequality reduction when each region's tax design is applied to its income distribution. The differences in ranking from Panel (a.ii) indicate that heterogeneous capital accumulations across regions significantly affect the redistributive capacity of their tax design.

Figure 3.13.: Tax Schedule Redistributive Effect on Different Pre-Tax Income Distributions. Gini Index.

(a) General Income (b) Total Income

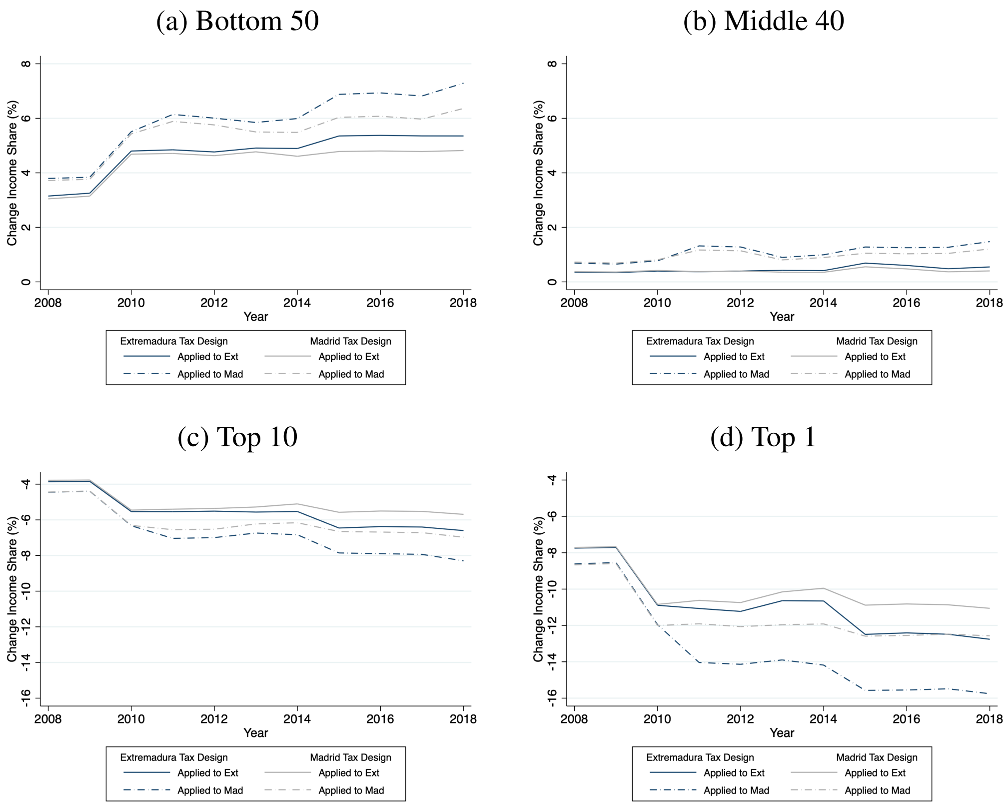


Notes: This figure shows the percentage reduction in the Gini index achieved by a given tax schedule when applied to different pre-tax income distributions. Gray lines illustrate the reduction in inequality achieved by applying Madrid's tax schedule to the pre-tax income distribution of Madrid (dashed line) and Extremadura (straight line). Blue lines illustrate the reduction in inequality achieved by Extremadura's tax schedule when applied to the pre-tax income distribution of Extremadura (straight line) and Madrid (dotted line). Larger Gini reductions indicate more substantial redistributive effects.

To document further how the pre-tax income distribution determines the redistributive effect achieved by a given tax design, we replicate the redistributive effect of Madrid and Extremadura tax designs when applied to each other's regional pre-tax income distributions. In Figure 3.13, gray lines represent the percentage reduction in pre-tax income inequality achieved by Madrid's tax schedule when applied to its pre-tax income distribution (dashed gray line) and when applied to Extremadura's income distribution (straight gray line). The difference between these two lines illustrates the effect of the pre-tax income distribution on redistribution. Likewise, blue lines represent the reduction in pre-tax income inequality achieved by Extramdura's tax schedule when applied to its income distribution (straight blue line) and Madrid's income distribution (dashed blue line). The difference between the straight (dashed) lines represents the difference in redistribution derived directly from applying different tax schedules on the same pre-tax income distribution.

To obtain comparable results, Figure 3.13 performs this exercise for two definitions of pre-tax income. Panel (a) only takes into account general income, and Panel (b) takes into account both general and capital income. In both cases, the pre-tax income distribution significantly impacts the redistributive effect of the tax design. Panel (b) shows that the inclusion of capital income significantly reduces the redistributive impact achieved by the tax. Furthermore, the different accumulations of capital income across regions mitigate the differences across regional tax designs.

Figure 3.14.: Tax Schedule Redistributive Effect on Different Pre-Tax Income Distributions. Shares of General Income.



Notes: This figure shows the percentage reduction in the share of general income of the Bottom 50, Middle 40, Top 10, and Top 1 percent of the income distribution achieved by a given tax schedule when applied to different pre-tax income distributions. Gray lines illustrate the percentage change in income shares derived from applying Madrid's tax schedule to the pre-tax income distributions of Madrid (dashed line) and Extremadura (straight line). Blue lines illustrate the percentage change in income shares achieved by Extremadura's tax schedule when applied to the pre-tax income distribution of Extremadura (straight line) and Madrid (dashed line).

Figure 3.14 replicates this exercise for the income shares of the Bottom 50 (Panel a), Middle 40 (Panel b), Top 10 (Panel c), and Top 1 (Panel d) percent of the income distribution. To obtain comparable results, this exercise only takes into account general income.[21] Blue lines represent the percentage change in general income shares after applying Extremadura's tax design to its pre-tax income distribution (straight line) and Madrid's pre-tax income distribution (dashed line). Gray lines represent the percentage change in general income shares after applying Madrid's tax design to its pre-tax income distribution (dashed line) and Extremadura's pre-tax income distribution (straight line).

[21]In Appendix D, Figure D.1 shows the results of this exercise when the analysis includes both general and capital income.

Several observations derive from Figure 3.14. First, the tax schedule of both regions has a significant redistributive effect as it increases the income share of the Bottom 50 percent while reducing the one of the Top 10, and especially the Top 1 percent. In either case, the effect for the Middle 40 percent is small. Second, the change in income shares due to each region's tax design is significantly affected by the pre-tax income distribution to which the tax design is applied. The distance between the dashed and straight blue (gray) lines indicates the differential effect of a given tax design when applied to different pre-tax distributions. Focusing on Panel (d), the larger distance between blue lines indicates a stronger redistributive potential of Extremadura's tax design than Madrid's design. Last, the straight blue and the dashed gray lines indicate the effect of each region's tax design when applied to their income distributions. Although both tax schedules have significantly different redistributive potentials, they achieve a more similar effect due to the interaction with their pre-tax income distributions.

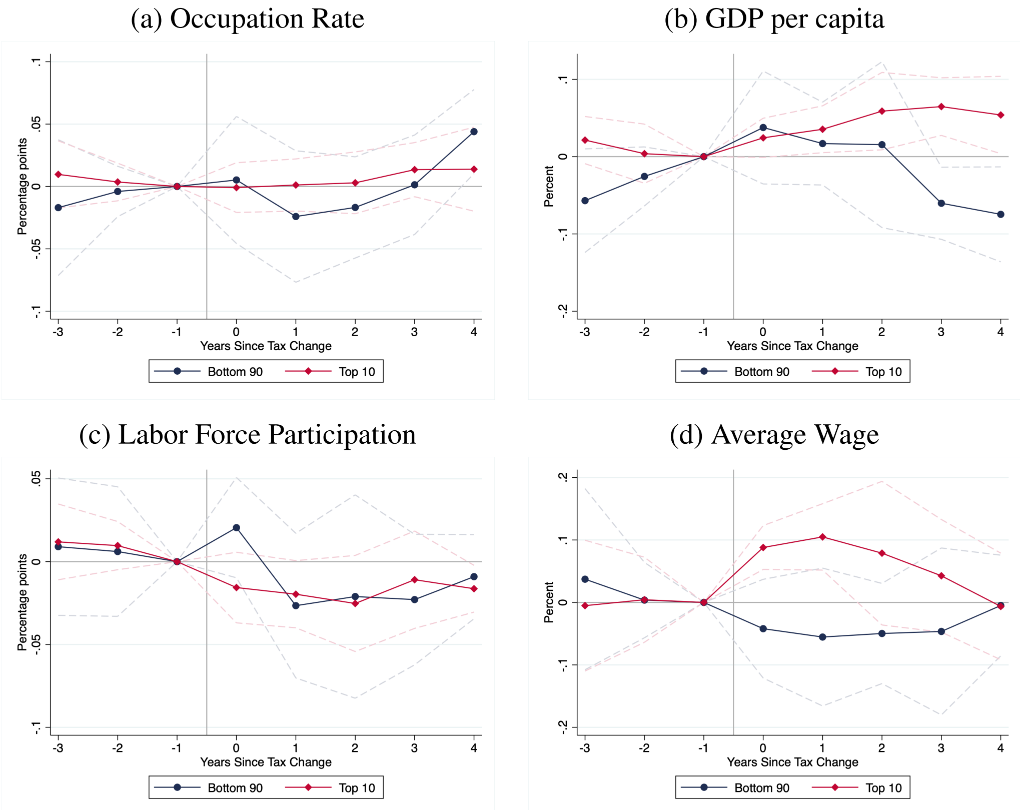
The evidence presented in this section shows the relevance of accounting for differences in pre-tax income distributions when assessing the redistributive design of tax schedules. While some regions deviate toward more (less) progressive designs, its redistributive effect is ultimately determined by the pre-tax income distribution to which it is applied. Regions with high marginal tax rates at the top of the distribution but with small shares of taxable income falling into the top brackets (i.e., Extremadura) can achieve lower redistributive effects than tax schedules with lower marginal tax rates at the top of the distribution but with more significant shares of taxable income subject to them (i.e., Madrid).

3.5.3. Effects of Tax Shocks on Economic Activity, Employment and Wages

This section presents the results exploring how tax changes for different income groups affect occupation, labor force participation, wages, and economic activity. Figure 3.15 shows the results of estimating Equation (3.3) for occupation rate (Panel a), GDP per capita (Panel b), labor force participation (Panel c) and average wage (Panel d). This set of results shows that tax shocks affecting either the Top 10 or Bottom 90 percent of the distribution don't significantly affect occupation, GDP per capita, or labor force participation. Nevertheless, Panel (d) shows that tax shocks affecting the Top 10 (Bottom 50) percent positively (negatively) affect average wages.

The results presented in this section are parallel to those in Zidar (2019) except for the effect on average wages. Our results show that the average wage responds to tax shocks affecting the top 10 percent of the income distribution. The increase

Figure 3.15.: Effects of Tax Shocks on Real Outcomes



Notes: Results from estimating Equation (3.3) following the methodology of Zidar (2019). Panel (a) shows the results for regional occupation rates, Panel (b) for regional GDP per capita, Panel (c) for regional labor force participation, and Panel (d) for regional average wage. Positive coefficients indicate an increase in the dependent variable after a tax shock affecting the Bottom 90 (blue) and the Top 10 (red) percent of the income distribution. Confidence intervals at the 95 percent level.

in average wages after a tax shock affecting this part of the distribution implies important incidence effects. Although increases in average wages can be interpreted as an increase in wages of individuals with stronger bargaining power, these results correspond to measures aggregated at the regional level and don't allow us to observe the effect along the income distribution.

3.6. Conclusion

This paper exploits the Spanish 2010 decentralization wave to shed new light on the role of sub-national governments in income redistribution. To identify the redistributive effect derived from granting normative power to heterogeneous sub-national regions, we use simulated counterfactual scenarios in a triple difference model where we compare the impact of the regional tax schedules relative to the counterfactual which would have emerged if they had mimicked the central government tax policy.

Baseline results using different inequality measures show an increase in the degree of redistribution achieved through the regional tax design. Still, the effect is relatively small compared to the overall impact of the tax system. We then move beyond aggregate measures and analyze the redistributive effect for different income groups. We find that regions' deviations from the central level tax design reduced inequality at both the top and bottom end of the distribution.

We include a counterfactual scenario where the pre-tax income distribution is kept constant in 2010 to isolate effects derived from potential behavioral responses and distribution changes. Our results show that changes in the pre-tax distribution did not significantly affect the decentralization effect on redistribution. However, the redistributive impact achieved by the Spanish PIT was limited by changes in the distribution itself.

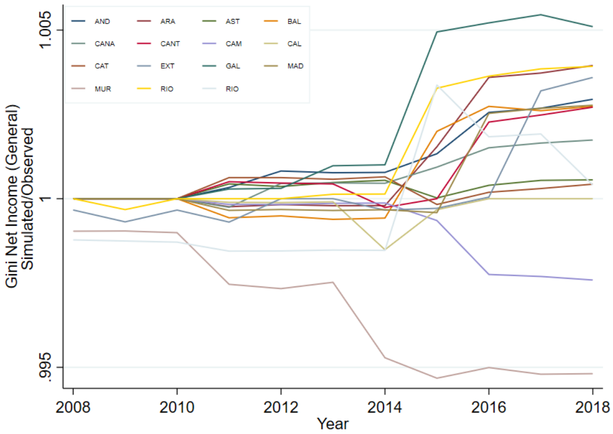
We further explore the role of the pre-tax income distribution as a factor determining redistribution by applying each region's tax design to a common pre-tax income distribution. This exercise allows us to perform two different observations. First, we can compare changes in redistribution across regions derived directly from heterogeneous tax schedules. Second, it shows evidence of the pre-tax income distribution as an important factor determining the redistributive capacity of a given tax design. This result points to the importance of pre-distributive policies in counteracting inequality increases and the relevance of analyzing the equity effects of tax shocks.

Last, we analyze the equity effect of tax shocks by exploiting exogenous variation in central government tax policies. We identify the impact of tax shocks by exploiting their heterogeneous effect across regions due to the existing differences in pre-tax income distributions. Our approach shows that the impact of these tax policies on employment, production, and labor force participation is relatively small. Nevertheless, the average wage responds to tax changes affecting the distribution's top 10 percent, implying important incidence effects.

Our results point toward two different avenues for further research. First, our analysis estimates the average decentralization effect on redistribution. Yet, regions used their normative power to deviate from the central-level design in different directions. While some regions implemented more progressive tax designs with high tax rates on larger incomes, others increased marginal tax rates for middle incomes or decreased them at the bottom of the income distribution. Thus, understanding the determinants of regional tax policy could help improve our knowledge of the implications of tax decentralization. Machine learning models provide interesting tools to disentangle the interaction of factors determining regional tax designs such as political preferences, adaptations to pre-tax distributions, or financial needs. Second, our analysis points toward significant incidence effects of tax hikes. Yet, our results are based on regional measures. Studying the employment and wage effects along the income distribution would help better identify the incidence of tax shocks for different population segments.

A. Descriptive Material

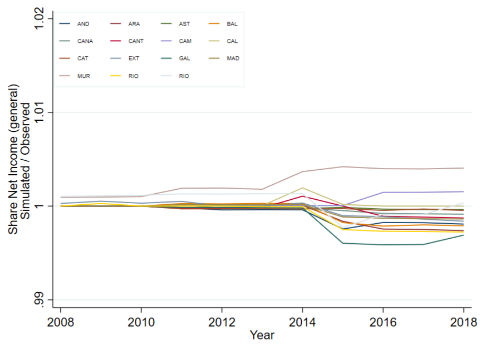
Figure A.1.: Differences in Redistribution from the Central Tax Design. General Income



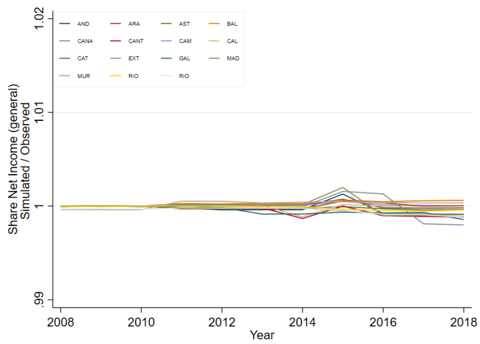
Notes: This figure shows, for each region, the evolution of the ratio between the after-tax Gini index in the counterfactual scenario where the region does not deviate from the central-level tax design and the after-tax Gini index in the observed scenario where regions use their normative power. Gini measures are relative to general income. Values larger than one imply higher inequality in the central level scenario, indicating regional deviations towards a more redistributive design.

Figure A.2.: Differences in Redistribution from the Central Tax Design. General Income

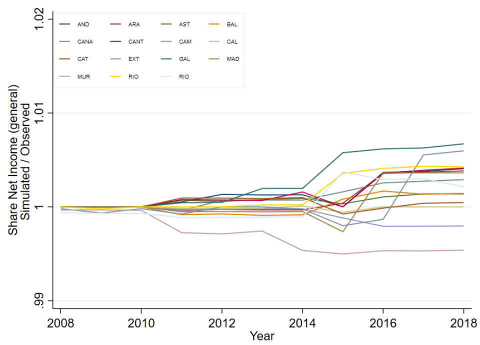
(a) Bottom 50



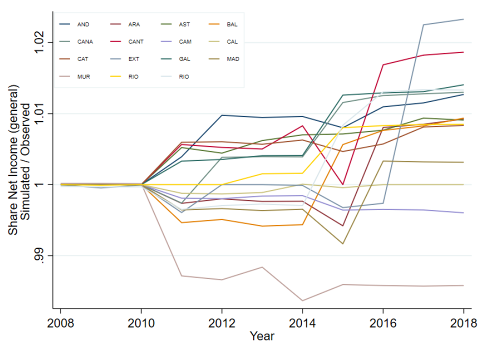
(b) Middle 40



(c) Top 10



(d) Top 1



Notes: This figure shows for each region and income group the evolution of the ratio between the after-tax income share in the counterfactual scenario where the region does not deviate from the central level tax design and the after-tax income share in the observed scenario where regions use their normative power. Values larger than one imply larger shares in the central level scenario than when regions use their normative power. Income measures correspond to general income. The Bottom 50 corresponds to the group p0p50, the Middle 40 to the group p50p90, the Top 10 to the group p90p100, and the Top 1 to the group p99p100.

Table A.1.: Regional Descriptive Statistics 2010

Region	N	Gross Income		Taxable Income		Total Liabilities		Net Income	
		Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
(a) General Income									
AND	3,491,428	19,573.64	18,479.67	14,875.68	17,689.93	2,521.15	6,225.81	17,052.49	12,692.54
ARA	770,786	21,600.52	20,294.05	16,986.11	19,246.89	3,158.99	6,893.68	18,441.53	13,805.04
AST	589,348	21,321.27	17,303.78	16,655.05	16,078.70	2,943.06	5,425.82	18,378.21	12,301.92
BAL	513,425	21,096.39	21,566.99	16,651.59	20,727.79	3,033.09	7,733.74	18,063.29	14,216.41
CANAR	856,504	19,894.23	17,265.35	15,384.02	16,477.42	2,640.39	5,685.19	17,253.85	11,948.08
CANT	308,161	21,195.84	17,047.22	16,574.85	15,965.90	2,927.87	5,351.82	18,267.97	12,073.40
CLEON	1,374,155	19,866.26	17,576.92	15,335.95	16,664.12	2,627.31	5,810.35	17,238.95	12,184.15
CMAN	980,751	19,378.51	15,351.80	14,679.31	14,478.36	2,432.34	4,643.24	16,946.17	11,063.29
CAT	3,911,559	23,491.63	29,700.27	18,873.16	28,880.01	3,704.30	11,448.80	19,787.33	18,638.05
VAL	2,372,088	19,632.94	21,305.51	15,033.00	20,484.51	2,604.65	7,641.82	17,028.30	14,114.06
EXTR	521,921	17,391.54	16,192.84	12,822.21	15,549.89	2,010.30	5,332.81	15,381.24	11,290.16
GAL	1,414,521	19,264.13	21,373.39	14,829.20	20,659.30	2,518.70	7,817.86	16,745.42	14,000.12
MAD	3,327,004	25,877.10	45,034.66	21,157.71	44,332.36	4,393.32	18,293.04	21,483.78	27,051.60
MUR	626,090	19,437.70	16,462.50	14,726.35	15,588.05	2,392.22	5,189.19	17,045.48	11,713.06
RIO	179,346	20,267.16	17,563.55	15,835.45	16,620.71	2,783.50	5,648.12	17,483.66	12,294.02
(b) Total Income									
AND	3,491,428	20,391.54	23,067.36	15,673.95	22,403.73	2,656.05	7,041.39	17,735.49	16,459.74
ARA	770,786	23,129.09	25,723.54	18,475.48	24,697.43	3,420.19	7,731.19	19,708.90	18,493.00
AST	589,348	22,343.61	21,319.61	17,644.26	20,272.46	3,114.51	6,146.90	19,229.10	15,568.99
BAL	513,425	22,320.22	26,904.94	17,842.42	26,160.50	3,246.72	8,584.46	19,073.50	18,821.18
CANAR	856,504	20,544.79	19,688.38	16,022.47	18,924.80	2,753.47	6,079.13	17,791.32	14,001.16
CANT	308,161	22,375.83	20,566.88	17,727.90	19,582.83	3,127.57	5,940.88	19,248.25	15,004.91
CLEON	1,374,155	21,015.08	20,020.09	16,453.81	19,158.97	2,809.19	6,205.94	18,205.89	14,253.91
CMAN	980,751	20,326.64	19,119.44	15,601.36	18,370.69	2,582.63	5,282.90	17,744.01	14,183.18
CAT	3,911,559	25,053.76	40,617.04	20,391.53	39,583.02	3,976.71	13,009.01	21,077.05	28,452.71
VAL	2,372,088	20,884.20	35,742.57	16,228.03	33,384.68	2,809.27	9,615.32	18,074.93	27,293.73
EXTR	521,921	18,111.69	19,439.36	13,526.93	18,846.41	2,121.36	5,823.03	15,990.33	14,080.51
GAL	1,414,521	20,158.38	25,721.02	15,704.07	25,085.54	2,664.84	8,468.51	17,493.54	17,828.02
MAD	3,327,004	27,492.16	11,0661.53	22,695.31	88,529.73	4,680.13	24,637.23	22,812.04	92,733.69
MUR	626,090	20,359.85	19,561.02	15,623.14	18,759.29	2,539.40	5,709.11	17,820.45	14,286.24
RIO	179,346	21,771.84	26,072.69	17,307.61	25,353.41	3,036.02	7,068.16	18,735.82	19,402.73

Notes: Descriptive statistics by Region. N corresponds to the number of tax filings after applying the corresponding weights. Data corresponds to the 2010 Muestra IRPF IEF-AEAT and includes non-tax filers. Panel (a) represents measures of income subject to the general tax base. Panel (b) includes capital income.

Table A.2.: Descriptive Statistics by Year

Year	N	Gross Income		Taxable Income		Total Liabilities		Net Income	
		Mean	Sd	Mean	Sd	Mean	Sd	Mean	Sd
(a) General Income									
2008	21,204,197	21,861.56	28,901.41	17,200.23	28,159.47	3,202.93	11,180.25	18,658.64	18,120.80
2009	21,115,650	21,667.66	31,090.97	17,009.42	30,395.76	3,156.11	12,201.08	18,511.54	19,289.72
2010	21,237,087	21,422.27	26,874.24	16,798.60	26,133.06	3,088.10	10,232.55	18,334.17	17,060.45
2011	21,480,194	21,477.38	28,169.02	16,887.87	27,420.57	3,141.56	11,355.59	18,335.81	17,344.36
2012	21,287,825	20,750.83	27,449.49	16,232.30	26,731.08	3,120.14	12,610.52	17,630.69	15,627.14
2013	21,022,663	20,650.46	28,314.47	16,136.81	27,600.57	3,072.61	13,074.14	17,577.85	16,017.37
2014	21,117,678	20,813.83	28,487.62	16,288.30	27,729.45	3,105.15	13,250.31	17,708.69	16,065.10
2015	21,409,547	21,390.53	49,719.73	16,796.48	49,486.27	2,959.95	21,270.81	18,430.57	28,812.96
2016	21,737,994	21,848.59	38,697.30	17,259.29	38,399.14	3,059.71	16,426.92	18,788.88	22,739.07
2017	22,266,671	22,346.96	55,575.91	17,765.62	55,360.90	3,178.39	25,184.62	19,168.57	30,812.84
2018	22,943,464	22,936.94	50,148.24	18,091.98	49,956.41	3,327.45	21,651.02	19,609.49	28,868.21
(b) Total Income									
2008	21,204,197	23,670.48	51,395.93	18,984.71	50,905.88	3,489.71	13,781.46	20,180.77	38,907.89
2009	21,115,650	23,324.10	54,699.61	18,630.14	54,086.55	3,414.56	14,814.24	19,909.53	41,381.14
2010	21,237,087	22,629.31	51,470.35	17,966.00	43,665.17	3,292.74	12,772.07	19,336.56	41,527.53
2011	21,480,194	22,809.92	51,518.48	18,187.08	50,849.09	3,372.93	14,760.32	19,436.99	37,897.64
2012	21,287,825	21,936.42	42,227.89	17,378.62	41,334.32	3,353.26	15,511.51	18,583.17	27,894.09
2013	21,022,663	21,741.20	46,027.79	17,175.23	44,438.70	3,282.98	16,634.13	18,458.22	30,811.88
2014	21,117,678	21,913.32	53,105.16	17,330.56	52,304.93	3,325.99	18,213.64	18,587.34	36,109.88
2015	21,409,547	22,571.77	71,481.88	17,919.77	70,501.67	3,149.84	24,654.96	19,421.93	48,541.52
2016	21,737,994	22,974.89	61,420.16	18,331.12	60,669.93	3,244.89	19,884.84	19,730.00	43,031.79
2017	22,266,671	23,600.29	77,509.23	18,949.01	76,903.95	3,389.11	28,312.27	20,211.18	51,372.07
2018	22,943,464	24,378.24	90,625.65	19,464.51	90,043.23	3,580.78	27,961.04	20,797.46	64,639.19

Notes: Descriptive statistics by year. N corresponds to the number of tax filings after applying the corresponding weights to each year's dataset. Data corresponds to the Muestra IRPF IEF-AEAT and includes non-tax filers. Panel (a) represents measures of income subject to the general tax base. Panel (b) includes capital income.

Table A.3.: Regional Distributions 2010. Capital Income and Total Income.

Region	Gini Gross		Bracket 1		Bracket 2		Bracket 3		Bracket 4	
	Capital	Total	Capital	Total	Capital	Total	Capital	Total	Capital	Total
AND	90.07	38.14	54.81	45.16	21.19	30.28	11.78	15.21	12.22	9.34
ARA	87.28	38.57	49.59	39.38	23.37	32.32	12.85	15.26	14.18	13.04
AST	87.84	36.70	47.85	38.22	28.08	37.91	12.19	15.52	11.89	8.35
BAL	89.67	37.66	47.31	42.38	23.67	29.82	13.07	15.76	15.96	12.04
CANAR	92.49	36.52	48.65	45.74	24.03	30.59	13.00	14.58	14.32	9.09
CANT	88.99	36.56	52.97	41.40	24.66	33.22	11.18	16.34	11.20	9.04
CLEON	83.24	36.37	56.17	44.82	24.59	32.41	11.11	14.73	8.13	8.04
CMAN	87.15	36.14	58.22	47.90	21.70	30.20	11.67	14.12	8.41	7.78
CAT	88.76	38.78	46.66	35.25	19.30	31.58	12.65	17.17	21.38	15.99
VAL	87.52	38.48	51.97	45.40	19.16	29.95	11.56	14.30	17.31	10.35
EXTR	88.85	37.48	59.03	52.65	21.22	28.40	10.02	11.74	9.73	7.21
GAL	87.55	37.51	52.89	47.02	21.86	29.52	11.87	14.20	13.38	9.26
MAD	90.44	40.04	36.02	29.66	23.73	32.11	11.60	19.20	28.65	19.03
MUR	89.01	37.07	55.51	47.04	19.61	30.35	12.35	14.49	12.53	8.12
RIO	86.96	37.65	50.45	43.17	22.02	31.28	10.85	15.06	16.69	10.49
TOTAL	88.94	38.69	48.00	40.10	21.71	31.24	11.97	16.07	18.33	12.59

Notes: This table shows basic descriptive inequality measures for each Spanish region and for Spain as a whole in year 2010. *"Capital"* represents income subject to the capital tax base, *"Total"* represents the sum of both capital and general income. All measures correspond to pre-tax income. The magnitudes are calculated using the Muestra IRPF IEF-AEAT of year 2010 and include non-tax fillers.

Table A.4.: Descriptive Statistics: Inequality Measures

(a) General Income

	Before Tax					After Tax			
Income	N	Mean	Sd	Min	Max	Mean	Sd	Min	Max
T1	229,431	164,470.813	458,485.438	68,632.641	73,728,928.000	104,694.625	253,864.063	47,177.902	41,668,364.000
T10	2,293,302	65,203.074	149,395.922	34,833.129	73,728,928.000	48,219.113	82,945.945	27,787.459	41,668,364.000
M40	9,177,316	26,907.137	7,020.333	14,557.960	48,665.629	23,294.270	5,212.956	12,902.967	48,609.820
B50	11,472,846	11,312.563	4,857.594	0.000	21,105.750	10,943.212	4,474.915	0.000	21,085.420
Full Distribution	22,943,464	22,936.943	50,148.242	0.000	73,728,928.000	19,609.492	28,868.209	0.000	41,668,364.000
Inequality measures									
T1	165	6.038	1.057	4.670	10.658	4.624	0.735	3.667	7.921
T10	165	27.359	1.293	24.964	32.320	24.036	0.928	22.138	27.546
M40	165	47.877	1.169	44.714	50.794	48.321	0.986	45.790	50.805
B50	165	24.764	0.737	22.718	26.409	27.643	0.712	25.925	29.479
GINI	165	36.695	1.208	34.728	40.983	32.099	0.976	30.291	35.459

(b) Total Income

	Before Tax					After Tax			
Income	N	Mean	Sd	Min	Max	Mean	Sd	Min	Max
T1	229,431	237,061.938	866,899.875	72,844.117	117,204,144.000	164,520.250	619,422.500	50,082.656	90,219,992.000
T10	2,290,235	75,614.477	280,108.031	35,635.066	117,204,144.000	56,696.125	199,632.297	28,545.049	90,219,992.000
M40	9,178,687	27,562.680	7,345.521	14,749.700	51,315.598	23,823.057	5,465.636	13,096.896	50,100.148
B50	11,474,542	11,604.564	4,842.854	0.000	21,652.299	11,212.114	4,439.661	0.000	21,631.230
Full Distribution	22,943,464	24,378.236	90,625.648	0.000	117,204,144.000	20,797.457	64,639.188	0.000	90,219,992.000
Inequality measures									
T1	165	7.307	1.713	4.984	14.782	5.936	1.449	3.978	12.234
T10	165	28.654	1.868	25.449	36.190	25.408	1.563	22.765	31.731
M40	165	46.778	1.513	41.813	50.246	47.186	1.352	42.484	50.238
B50	165	24.568	0.806	21.602	26.340	27.405	0.714	24.930	28.883
GINI	165	38.141	1.530	35.936	44.708	33.657	1.263	31.599	39.094

Notes: Inequality measures at the regional level. Summary statistics of income corresponding to year 2018. Summary statistics of inequality measures corresponding to years 2008 to 2018. Panel (a) corresponds to income subject to the general tax base. Panel (b) includes capital income.

Table A.5.: Tax Calculator Goodness of Fit

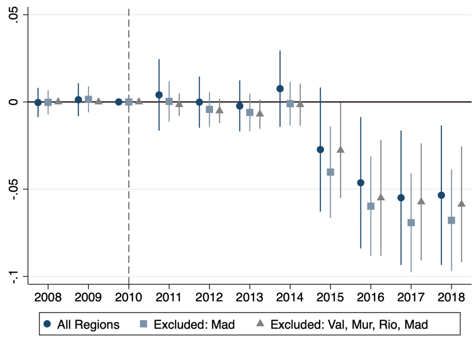
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
General Liab Central	0.999***	0.999***	0.999***	0.999***	0.999***	0.999***	0.999***	1.000***	0.999***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-3.130***	-3.572***	-2.722***	-2.782***	-4.017***	-4.177***	-4.031***	-6.210***	-5.300***	-6.597***	-6.065***
	(0.016)	(0.016)	(0.013)	(0.014)	(0.019)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
R2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
N	19,023,343	18,935,469	18,870,882	19,158,128	18,995,469	18,725,623	18,851,404	18,995,907	19,132,479	19,526,068	20,252,685
General Liab Region	0.999***	0.999***	0.999***	0.999***	0.999***	0.999***	0.999***	1.000***	0.999***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.741***	-1.989***	-2.643***	-2.675***	-2.931***	-3.266***	-3.260***	-5.689***	-5.091***	-6.668***	-6.186***
	(0.010)	(0.009)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.017)	(0.017)	(0.018)	(0.018)
R2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
N	19,023,343	18,935,469	18,870,882	19,158,128	18,995,469	18,725,623	18,851,404	18,995,907	19,132,479	19,526,068	20,252,685
Capital Liab Central	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.003***	1.004***	1.003***	1.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.004***	-0.004***	14.190***	13.340***	14.540***	15.880***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.094)	(0.091)	(0.101)	(0.107)
R2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.995	0.995	0.995	0.997
N	19,023,343	18,935,469	18,870,882	19,158,128	18,995,469	18,725,623	18,851,404	18,995,907	19,132,479	19,526,068	20,252,685
Capital Liab Central	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***	1.003***	1.004***	1.003***	1.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***	-0.002***	-0.002***	14.780***	13.320***	14.490***	15.860***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.097)	(0.091)	(0.101)	(0.107)
R2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.995	0.995	0.995	0.997
N	19,023,343	18,935,469	18,870,882	19,158,128	18,995,469	18,725,623	18,851,404	18,995,907	19,132,479	19,526,068	20,252,685

Notes: Predictive power of the tax calculator by year. Estimates resulting from regressing the output of the tax calculator against the data reported by the Muestra IRPF IEF-AEAT data set including non-tax filers. The constant represents the underestimation or overestimation of the tax calculator. Results reported for simulations of liabilities corresponding to the central level general tax schedule (*"General Liab Central"*), central level capital tax schedule (*"Capital Liab Central"*), regional level general tax schedule (*"General Liab Regional"*), and regional level capital tax schedule (*"Capital Liab Regional"*). Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

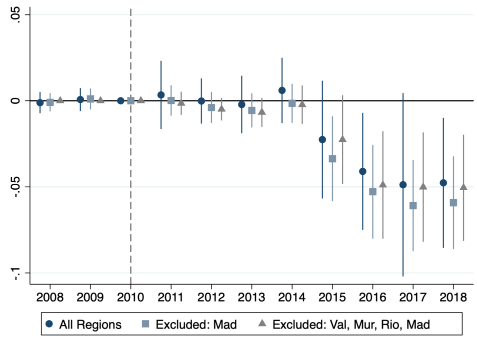
B. Baseline Model Estimation: Additional Results

Figure B.1.: Dynamic Results: Effect of Decentralization on Redistribution Measured by Changes in Gini Indices

(a) General Income



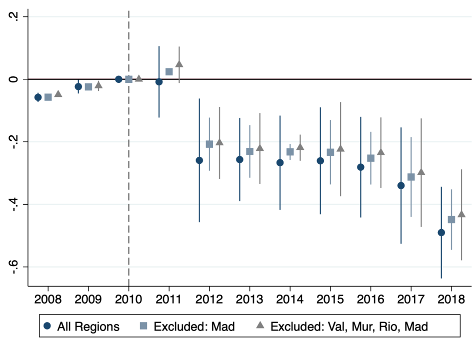
(b) Total Income



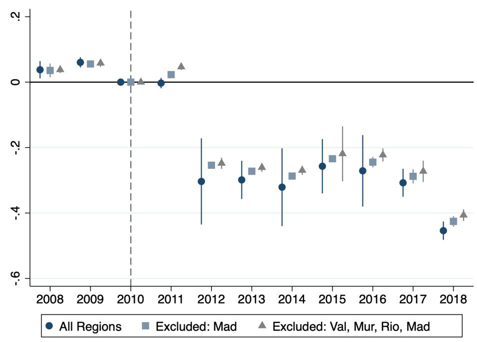
Notes: Results correspond to the estimation of Equation (3.2). Coefficients are the marginal change in redistribution derived from regions' normative power relative to 2010. Inequality is measured by the Gini Index. Panel (a) reports the results when inequality measures only include general income. Panel (b) reports the results when inequality measures include general and capital income. Negative coefficients indicate a larger reduction in the after-tax Gini index relative to the reduction achieved when regions don't use their normative power. Coefficients estimated while controlling for each bracket income share, regional, and time-fixed effects. Standard errors clustered at the region-year level and bracket-year-income level. Confidence intervals at the 95 percent.

Figure B.2.: Central-level Redistributive Effect Measured by Change in Gini Indices. Base 2010.

(a) General Income



(b) Total Income



Notes: Redistributive effect achieved by the Spanish PIT system in the scenario where regions do not deviate from the central level design. Inequality measures taking into account general income (Panel a) and general and capital income (Panel b). Inequality measured by regional Gini indices. Estimates relative to the year 2010. Negative coefficients indicate a larger reduction in the after-tax Gini index relative to the reduction achieved in the year 2010. Coefficients correspond to the estimation of Equation (3.2) when controlling for each bracket income share. Standard errors clustered at the region-year level and bracket-year-income level. Confidence intervals at the 95 percent level.

Table B.1.: Effects of Decentralization on Redistribution Measured by Income Shares. Excluded Regions.

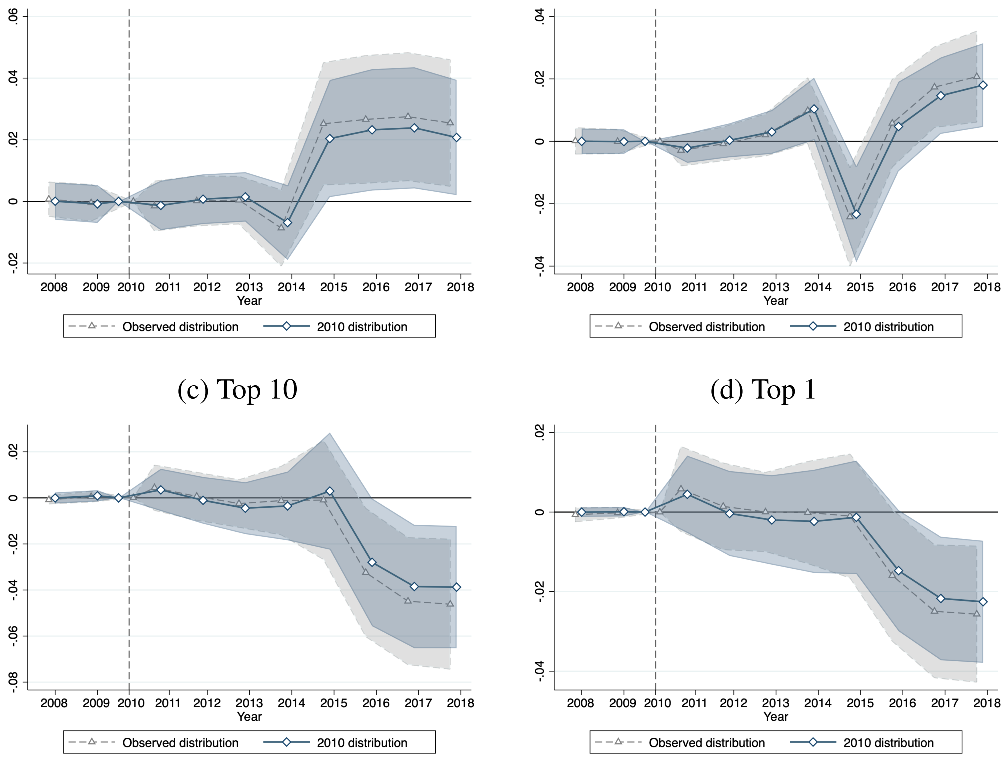
	(a) Share of General Income				(b) Share of Total Income			
	B50	M40	T10	T1	B50	M40	T10	T1
AT	2.712***	0.420***	-3.132***	-1.284***	2.660***	0.347***	-3.007***	-1.188***
	(0.005)	(0.006)	(0.009)	(0.025)	(0.003)	(0.005)	(0.009)	(0.008)
AT*NP	0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D1*AT	0.122***	-0.063***	-0.060	-0.0201	0.167***	-0.010**	-0.157***	-0.108***
	(0.008)	(0.017)	(0.039)	(0.040)	(0.001)	(0.005)	(0.016)	(0.010)
D1*AT*NP	-0.000	0.008***	-0.007***	-0.006**	-0.000	0.007***	-0.007***	-0.006**
	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
D2*AT	0.233***	-0.069***	-0.164***	-0.086**	0.240***	-0.013**	-0.226***	-0.157***
	(0.012)	(0.023)	(0.044)	(0.043)	(0.004)	(0.006)	(0.013)	(0.009)
D2*AT*NP	0.032***	0.010	-0.043***	-0.029***	0.029***	0.007	-0.036***	-0.023***
	(0.005)	(0.007)	(0.009)	(0.004)	(0.005)	(0.006)	(0.008)	(0.004)
Constant	24.950***	48.110***	26.940***	5.740***	24.850***	47.170***	27.980***	6.726***
	(0.080)	(0.053)	(0.088)	(0.059)	(0.083)	(0.117)	(0.155)	(0.153)
Observations	1,936	1,936	1,936	1,936	1,936	1,936	1,936	1,936
R-squared	0.968	0.955	0.968	0.959	0.962	0.915	0.926	0.881
RFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded Observations	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Results from estimating Equation (3.1) when the dependent variables are the shares of income accumulated at the B50, M40, T10, and T1 percent of the distribution. Excluded regions are Madrid, Valencia, Murcia, and La Rioja. Panel (a) reports measures of income subject to the general tax base. Panel (b) includes capital income in the analysis. Measures of income shares are defined at the regional level. Controls include the share of gross income corresponding to the general tax base falling into each tax bracket as defined by the 2010 tax schedule. *AT* is a dummy taking a value of one if the inequality measure corresponds to after-tax income and zero if it corresponds to pre-tax income. *NP* is a dummy taking a value of one if the inequality measure corresponds to the scenario where regions use their normative power and zero if regions follow the central-level tax design. *D* is a dummy variable taking a value of one for the after-decentralization period. *D*1 is a dummy variable taking a value of one for the period immediately after the 2010 decentralization (2011 to 2014). *D*2 is a dummy variable taking a value of one for the period after the 2014 PIT reform (2015 to 2018). Standard errors clustered at the region-year level and bracket-year-income level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C. Exclusion of Behavioral Responses: Additional Results

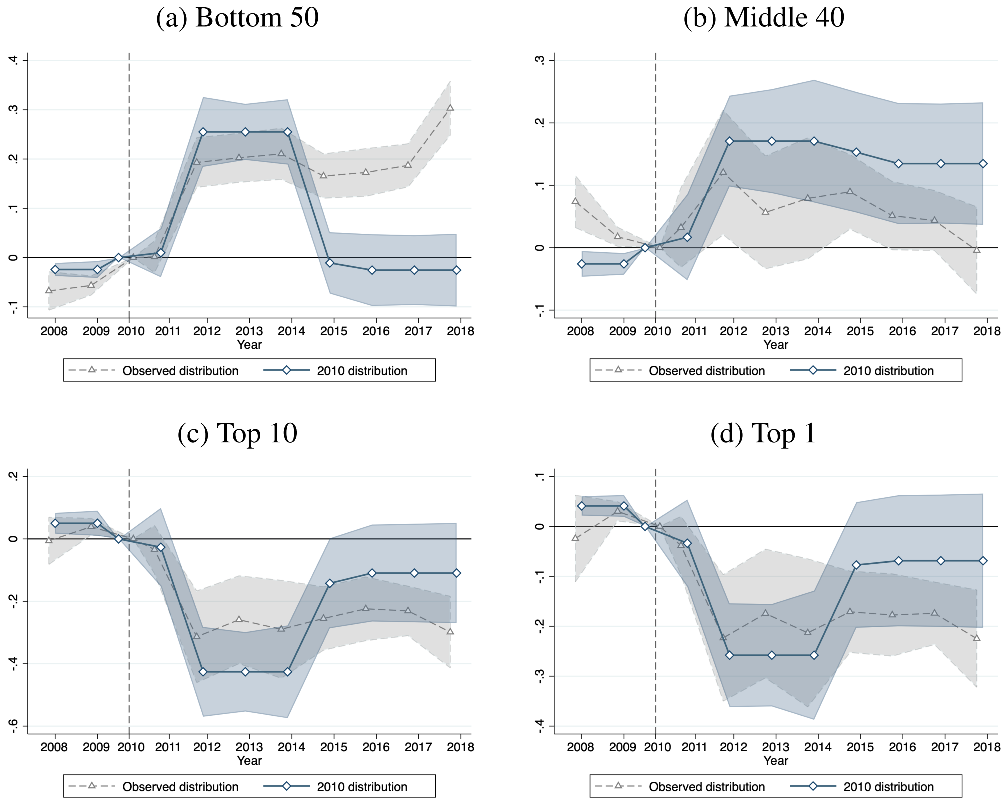
Figure C.1.: Effect of PIT Decentralization on Redistribution

(a) Bottom 50 (b) Middle 40 (c) Top 10 (d) Top 1



Notes: Results correspond to the estimation of Equation (3.2) adapted to include the counterfactual scenario where the pre-tax income distribution is kept constant at year 2010. Inequality is measured by the income shares of the Bottom 50 (Panel a), Middle 40 (Panel b), Top 10 (Panel c), and Top 1 (Panel d) percent of the income distribution. Income shares computed at the regional level taking into account both general and capital income. Reported coefficients represent the marginal change in redistribution derived from regions' normative power relative to year 2010. Negative coefficients indicate a larger reduction in the after-tax income share relative to the reduction achieved in the situation where regions do not use their normative power. Coefficients represented by a rhombus correspond to the scenario where the pre-tax income distribution is fixed at year 2010. Triangular coefficients correspond to the scenario where the pre-tax income distribution is the one observed each year. Coefficients estimated while controlling by each bracket income share, regional and time fixed effects. Standard errors clustered at the region-year level and bracket-year-income level. Confidence intervals at the 95 percent.

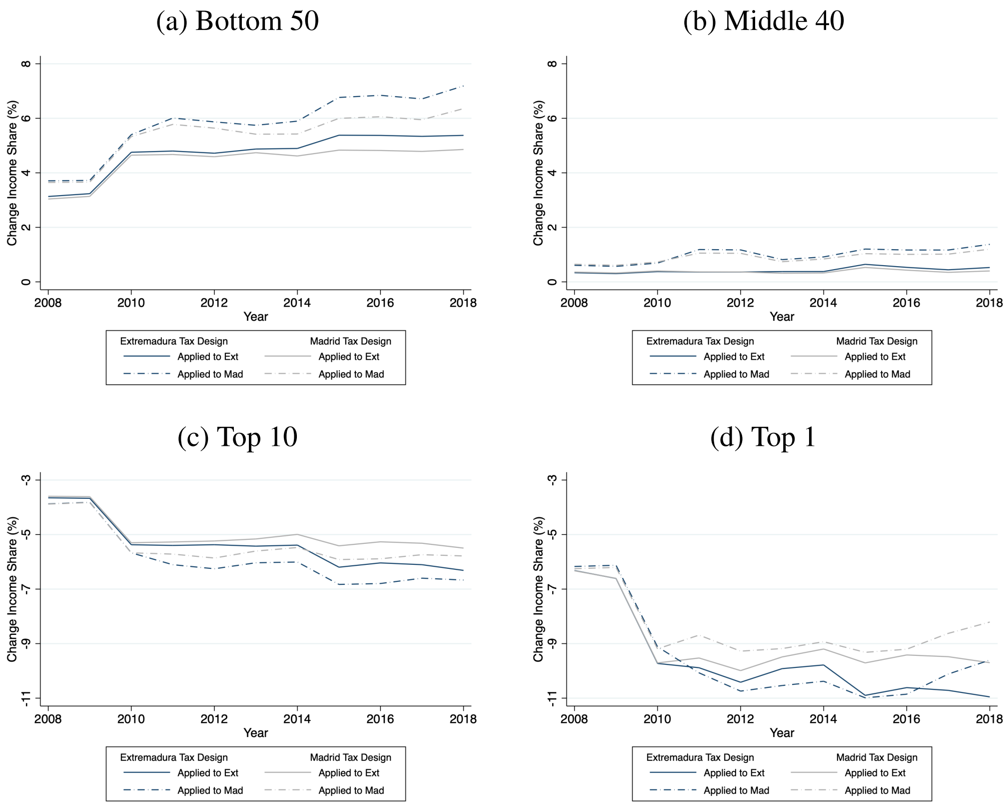
Figure C.2.: Redistributive Effect of the Central Level Tax Design



Notes: Results correspond to the estimation of Equation (3.2) adapted to include the counterfactual scenario where the pre-tax income distribution is kept constant at year 2010. Inequality is measured by the income shares of the Bottom 50 (Panel a), Middle 40 (Panel b), Top 10 (Panel c), and Top 1 (Panel d) percent of the income distribution. Coefficients represent the change in income shares due to the application of the central level tax design. Coefficients represented by a rhombus correspond to the scenario where the pre-tax income distribution is fixed at year 2010. Triangular coefficients correspond to the scenario where the pre-tax income distribution is the one observed each year. Income shares computed at the regional level taking into account both general and capital income. Coefficients estimated while controlling by each bracket income share, regional and time fixed effects. Standard errors clustered at the region-year level and bracket-year-income level. Confidence intervals at the 95 percent.

D. Differences in Pre-Tax Distributions

Figure D.1.: Tax Schedule Redistributive Effect on Different Pre-Tax Income Distributions. Shares of Total Income.



Notes: This figure shows the percentage reduction in the total income shares of the Bottom 50, Middle 40, Top 10, and Top 1 percent of the income distribution achieved by a given tax schedule when applied to different pre-tax income distributions. Gray lines illustrate the percentage change in income shares achieved by applying Madrid's tax schedule to the pre-tax income distributions of Madrid (dashed line) and Extremadura (straight line). Blue lines illustrate the percentage change in income shares achieved by Extremadura's tax schedule when applied to the pre-tax income distribution of Extremadura (straight line) and Madrid (dashed line).

E. Redistribution at the National Level

Table E.1.: Effect of Decentralization on Redistribution Measured by Gini Indices. National Income Distribution.

	(a) Genreal Income			(b) Total Income		
	(1)	(3)	(5)	(1)	(3)	(5)
AT	-4.686***	-4.686***	-4.686***	-4.498***	-4.498***	-4.498***
	(0.020)	(0.020)	(0.020)	(0.015)	(0.016)	(0.016)
AT*NP	0.012***	0.012***	0.012***	0.010***	0.010***	0.010***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
D*AT	-0.312***			-0.394***		
	(0.056)			(0.053)		
D*AT*NP	0.003			0.005		
	(0.006)			(0.005)		
D1*AT		-0.239***	-0.239***		-0.349***	-0.349***
		(0.067)	(0.067)		(0.080)	(0.080)
D1*AT*NP		0.010*	0.010*		0.010**	0.010**
		(0.005)	(0.005)		(0.004)	(0.004)
D2*AT		-0.385***	-0.385***		-0.438***	-0.438***
		(0.067)	(0.067)		(0.060)	(0.060)
D2*AT*NP		-0.004	-0.004		-0.000	-0.000
		(0.009)	(0.009)		(0.009)	(0.009)
Constant	37.900***	37.900***	37.900***	39.490***	39.490***	39.490***
	(0.020)	(0.017)	(0.017)	(0.019)	(0.018)	(0.018)
Observations	176	176	176	176	176	176
R-squared	0.999	1.000	1.000	0.999	0.999	0.999
RFE	Yes	Yes	Yes	Yes	Yes	Yes
TFE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Excluded Observations	No	No	VAL MUR RIO MAD	No	No	VAL MUR RIO MAD

Results from estimating Equation (3.1). Inequality is measured by the Gini Index of general income (Panel a) and total income (Panel b). Inequality measures computed at the national level. Controls include the share of gross income subject to the general tax rate falling into each tax bracket. Tax brackets are defined based on the 2010 tax schedule. AT is a dummy taking a value of one if the inequality measure corresponds to after-tax income and zero if it corresponds to pre-tax income. NP is a dummy taking a value of one if the inequality measure corresponds to the scenario where regions use their normative power and zero if regions follow the central-level tax design. D is a dummy variable taking a value of one for the after-decentralization period. $D1$ is a dummy variable taking a value of one for the period immediately after the 2010 decentralization (2011 to 2014). $D2$ is a dummy variable taking a value of one for the period after the 2014 PIT reform (2015 to 2018). Standard errors clustered at the region-year level and bracket-year-income level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.2.: Effect of Decentralization on Redistribution Measured by Income Shares. National Income Distribution.

	(a) Share of General Income				(b) Share of Total Income			
	B50	M40	T10	T1	B50	M40	T10	T1
AT	2.867***	0.603***	-3.470***	-1.557***	2.792***	0.509***	-3.301***	-1.430***
	(0.002)	(0.031)	(0.033)	(0.028)	(0.014)	(0.020)	(0.016)	(0.011)
AT*NP	-0.009***	0.002***	0.007***	0.001***	-0.008***	0.003***	0.005***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D1*AT	0.158***	0.041	-0.199**	-0.160***	0.214***	0.110**	-0.324***	-0.273***
	(0.039)	(0.044)	(0.064)	(0.048)	(0.049)	(0.037)	(0.069)	(0.053)
D1*AT*NP	-0.005	-0.005***	0.010**	0.010***	-0.005	-0.005***	0.010***	0.009***
	(0.003)	(0.001)	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)
D2*AT	0.276***	0.012	-0.288***	-0.250***	0.285***	0.097***	-0.383***	-0.353***
	(0.048)	(0.034)	(0.049)	(0.041)	(0.042)	(0.021)	(0.038)	(0.034)
D2*AT*NP	0.012***	-0.015	0.003	0.006	0.009***	-0.016	0.007	0.009
	(0.002)	(0.011)	(0.013)	(0.005)	(0.002)	(0.010)	(0.012)	(0.005)
Constant	24.120***	47.460***	28.420***	6.880***	23.830***	46.250***	29.92***	8.394***
	(0.011)	(0.007)	(0.013)	(0.010)	(0.011)	(0.006)	(0.014)	(0.011)
Observations	176	176	176	176	176	176	176	176
R-squared	1.000	0.999	1.000	0.999	0.999	0.999	0.999	0.999
RFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded Observations	No	No	No	No	No	No	No	No

Results from estimating Equation (3.1) when the dependent variables are the shares of income accumulated at the B50, M40, T10, and T1 percent of the distribution. Inequality measures computed at the national level. Panel (a) corresponds to income shares of income subject to the general tax base. Panel (b) includes capital income in the analysis. Controls include the share of gross income corresponding to the general tax base falling into each tax bracket as defined by the 2010 tax schedule. *AT* is a dummy taking a value of one if the inequality measure corresponds to after-tax income and zero if it corresponds to pre-tax income. *NP* is a dummy taking a value of one if the inequality measure corresponds to the scenario where regions use their normative power and zero if regions follow the central-level tax design. *D* is a dummy variable taking a value of one for the after-decentralization period. *D*1 is a dummy variable taking a value of one for the period immediately after the 2010 decentralization (2011 to 2014). *D*2 is a dummy variable taking a value of one for the period after the 2014 PIT reform (2015 to 2018). Standard errors clustered at the region-year level and bracket-year-income level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4. Blowing in the Wind: Revenue Windfalls and Local Responses from Wind Farm Development

4.1. Introduction

Renewable energy production technologies play a central role in the transition towards a decarbonized paradigm, offering global benefits by offsetting greenhouse gas emissions associated with conventional technologies.[1] Among these renewable sources, wind power is of particular interest as it is recognized as one of the most environmentally friendly sources of energy generation.[2] However, while wind infrastructure holds significant potential for clean energy generation, its development can also create negative local externalities. Consequently, new infrastructure initiatives often encounter opposition and conflict with local residents, resulting in a misallocation of renewable energy investment and higher deployment costs (Jarvis et al., 2021).

From a socioeconomic perspective, the development of this type of infrastructure, often located in rural areas, has been frequently presented as an opportunity for economic activity and employment creation in those regions. However, the realization of these benefits for host communities is not automatic. In addition to the visual and noise impacts associated with wind infrastructure, the displacement of potential alternative land uses and the perception of wind as a common good contribute to the demand from local communities for compensation (Ejdemo and Söderholm, 2015). Moreover, the perception of inequality and fairness in the distribution of benefits from wind energy projects are found to prompt local opposition to the installation of wind farms (Clausen and Rudolph, 2020; Wolsink, 2007).

In this paper, I study the local impact of large renewable energy projects on municipal finances and local tax responses. To do so, I focus on the development

[1] Cullen (2013) quantifies the emissions offset by wind power, and Novan (2015) quantifies the marginal external benefit of wind turbines and solar panels on pollution.

[2] See Rahman et al. (2022) or Schiermeier et al. (2008) for a review of the environmental impact of electrical power plants based on renewable energy sources.

of wind farms in Spain, a country that experienced a rapid growth in its wind energy sector between 2000 and 2013, leading to its position as the second-largest European country in terms of installed wind capacity. I use difference-in-differences and event-study methodologies which exploit spatial and temporal variations in the development of wind energy production installations to provide a clear causal identification of their local effects.

By exploiting the Spanish setting, this analysis contributes to understanding the impact wind investments have on host municipalities. This is particularly relevant in the absence of specific compensation mechanisms to offset the costs associated with such infrastructure. The lack of significant local employment effects (Fabra et al., 2023) suggests that, at the local level, the impact of such investments can take place mainly through income flows accumulating to landowners, local ownership stakes in the plant, or through an improvement in municipal finances (Mauritzen, 2020). In this context, understanding to what extent host municipalities can financially benefit from wind farm development is of primary interest. Resources generated from this type of infrastructure can be used to indirectly compensate local communities via increases in public expenditure and reductions in citizens' fiscal pressure.

More specifically, I use data from 1994 to 2020 for local budgets to investigate how municipal revenue is affected by the development of wind farms in their territory. I link this data to the development of wind farms by using information from the Spanish Register of Energy Producers, which provides the timing, location, and capacity of the universe of wind power plants in Spain. Baseline results show that, on average, wind farm development leads to a 30 percent increase in municipal revenue per capita. This effect, which already appears during the construction of a new installation, is persistent over time and follows an increasing trend once the new infrastructure is under operation.

These results are consistent with the strand of literature analyzing natural-resource windfalls.[3] Although positive effects on local revenue are present in either case, analyzing the effect of wind installations is especially relevant due to their substantial differences in project durability and local employment and wage effects. While the impact of wind farms on the local labor market is rather limited, fossil fuel booms and busts often come with large effects (Brown et al., 2014; Komarek, 2016; Marchand and Weber, 2020; Weber et al., 2016). In terms of project durability, shocks associated to fossil fuels often decrease as the natural resource is exhausted. This is not the case for wind installations. In the case of wind turbines, the effects may be more permanent due to their nature, allowing for continued investment through re-powering in locations with high winds and existing installations (Mauritzen,

[3] See for example Bartik et al. (2019) or Newell and Raimi (2015) for analysis focused on the shale oil and gas booms.

2020).

After identifying the aggregate effect on revenue, I decompose the results between the different revenue instruments that could potentially be affected by the construction of wind farms. Results show that the positive effect on municipal revenue is driven by different channels along the lifetime of the wind farm.[4] During the construction phase, the increase in total revenue is mainly driven by a larger yield from the construction tax. However, once the operations and maintenance phase starts, the effect takes place through increases in revenue generated by direct taxes and capital income.

Next, I investigate whether municipalities react to the broadening of the tax base derived from the development of wind farms to indirectly compensate inhabitants by modifying the tax rates under their discretion to decrease fiscal pressure on local inhabitants. To do so, I focus on the property tax, which is the main source of municipalities' own revenue, amounting to an average of 23 percent of total municipal revenue in 2019. More precisely, I analyze the tax rates associated with the different property tax categories by exploiting municipal tax rate data obtained from the Spanish Tax Agency. I find that receiving municipalities react to wind energy developments by increasing tax rates associated with this type of infrastructure (i.e., the special category property tax) close to maximum levels while decreasing tax rates associated with urban and rural property. The change in property tax rates implies that the effect on revenue is not only mechanical due to a broadening of the tax base but is complemented by local tax responses.

These results complement previous literature analyzing reactions to large capital-intensive projects through local tax responses. Langenmayr and Simmler (2021) exploit the development of the German wind energy sector and identify increases in municipal corporate taxes after the development of this type of non-mobile capital investment. By analyzing the different categories of the property tax, I show that local tax responses take place both through increases in the tax rates directly targeting capital-intensive projects as well as by alleviating the fiscal pressure associated to other property categories.

Last, I investigate municipalities' use of this new revenue to identify whether it is channeled toward policies directly benefiting local residents. Benefits to receiving communities can extend beyond the creation of employment opportunities if additional resources derived from the development of this type of infrastructure are used to redistribute income to hosting communities through improvements in the provision of public goods and services. The results show that, in aggregate terms, municipali-

[4] The IEC 61400[1] standard sets the design lifetime of a turbine in 20 years. This can be extended depending on environmental factors and the correct maintenance procedures being followed. See Ziegler et al. (2018) for a review on the lifetime extension of onshore wind turbines.

ties used this new source of revenue to increase total expenditure per capita by 14 percent. By decomposing the increase in expenditure into its different categories, I show that these resources were mainly used to increase current expenditure and real investment.

This paper contributes to the ongoing debate on the local impact of wind farms by providing a country-wide analysis of their effect on local finances. Although a developing body of literature has started exploring the effect of wind farms on local public finances, previous research has mainly centered on housing values and employment.[5] Studies focusing on European countries tend to point toward negative housing value effects (Dröes and Koster, 2021; Jarvis et al., 2021), yet consensus in the strand of literature analyzing employment effects is limited. Results on employment effects are mild and tend to differ conditional on the empirical methodology used and the level of analysis.[6] Focusing on the months surrounding the opening of wind farms in Spain, Fabra et al. (2023) find no increases in employment at the municipality level. In the case of Portugal, Costa and Veiga (2021) find short-term employment effects during the construction phase and a very small and sustained impact during the operations and maintenance phase.

The body of literature documenting increases in the local tax base and local revenues derived from wind farm development mostly focuses on specific regions or projects in the U.S. (see for example E. J. Brunner and Schwegman (2022) and Shoeib et al. (2022), or De Silva et al. (2016)).[7] E. J. Brunner and Schwegman (2022) examine how county governments respond to increases in the local tax base generated by the universe of U.S. wind farm installations. My results are consistent with their findings that wind farms led to large increases in county revenue. Nevertheless, they document increases in property values that are inconsistent with findings in European countries. In the U.S. setting, counties' provision of public goods and services includes spending on infrastructure such as highways or hospitals, which can lead to increases in housing prices due to citizens' valuation of locally provided public goods and sorting into counties with higher provisions. In the Spanish case, this type of public spending is assigned to higher administrative levels, and municipal competencies are limited to infrastructure such as sports facilities, public parks, or

[5] For studies focusing on housing values see for example Dröes and Koster (2021), Gibbons (2015), Jarvis et al. (2021), Jensen et al. (2018), and Sunak and Madlener (2016). For studies focusing on employment effects, see, for example, Allan et al. (2020), Brown et al. (2012), Costa and Veiga (2021), Fabra et al. (2023), and Hartley et al. (2015).

[6] See for example Lehr et al. (2012) and Slattery et al. (2011) for input-output approaches; Ejdemo and Söderholm (2015) for analysis based on a specific project; Copena and Simón (2018) for analysis based on participatory qualitative research; or Shoeib et al. (2022) for a matching approach.

[7] In the European context, Costa and Veiga (2021) report both short and long-term positive impacts of wind energy investment on total revenues of Portuguese municipalities where a special tax on 2.5 percent of total wind revenue has to be paid to receiving municipalities.

civic centers.

My results have important policy implications and contribute to the ongoing debate on the local impact of wind farms by showing that host municipalities financially benefit from their development. The revenue windfalls generated by this type of infrastructure, which are partially driven by increases in the tax base, are complemented by local tax responses as municipalities use their normative capacity to maximize the revenue generated from this type of energy installation. By analyzing the use that municipalities make of these extra financial resources, I show that it is targeted toward compensating host communities through increases in real investment and decreases in fiscal pressure. Yet, municipalities' competencies in terms of fiscal autonomy and public expenditure capacity are limited, and conflicts around planned investments are still present. The results presented in this paper point to the need to design mechanisms that can help compensate for local costs, mitigate local objections, and minimize conflicts around planned investments with the goal of moving toward a more optimal energy transition.

The rest of the paper is structured as follows. Section 4.2 describes the development and characteristics of the Spanish wind energy sector. Section 4.3 presents the data. Section 4.4 discusses the empirical strategy. Section 4.5 presents the baseline results, the analysis of local tax responses, and the decomposition of the effect between revenue and expenditure categories. Last, Section 4.6 concludes.

4.2. Institutional Context

4.2.1. Wind Farm Development

Wind power installation in Spain has witnessed significant growth over the past two decades, positioning the country as the second-largest in Europe in terms of installed wind capacity. The largest share of the installed capacity occurred between 1998 and 2012 and picked up again in 2018, resulting in 27 gigawatts by 2020. The discontinuation of support schemes and incentives for renewable investments marked the end of the first installation wave in 2012. Starting in 2018, a new set of regulations revitalized wind power development. The updated legal framework incorporates an auction system that ensures remuneration to cover production costs and guarantees a reasonable yield for renewable installations. Within this new framework, the development of renewable energies is projected to continue expanding in the forthcoming years, aiming to achieve the target of 50 gigawatts of installed wind power by 2030, as established by the Spanish National Integrated Energy and Climate Plan.

Administrative permits to develop new wind power plants are granted by the Regional Government of the Autonomous Community where the plant has to be located.[8] The issuance of administrative authorizations is contingent upon obtaining a positive environmental impact statement. This report evaluates the integration of environmental aspects of the project and determines the conditions to be established for the adequate protection of the environment and natural resources during the facility's execution and operation. Concerning land occupation, developers can reach bilateral agreements with landowners or apply for the public utility declaration of the project. While the public utility status enables the expropriation of the necessary land to develop the project, bilateral agreements with landowners generally offer a more cost-efficient approach.

As of 2020, the 1,201 wind power plants installed in Spanish territory were concentrated in 505 municipalities.[9] Figure 4.1 illustrates the spatial distribution of wind farms across the territory. Panel (a) documents the first year a wind farm was installed in each affected municipality. Panel (b) documents each municipality's accumulated wind power per capita in 2020. Besides the expected concentration of this type of infrastructure in areas with higher wind potential, Figure 4.1 does not show evidence of specific geographical patterns in the development of the sector.

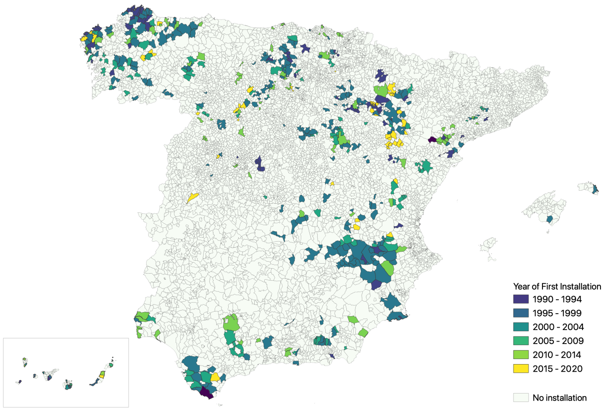
Table 4.1 presents summary statistics on municipal characteristics prior to the establishment of wind farms. In population terms, the affected municipalities are predominantly small. Out of the 505 municipalities affected, 468 have less than 10,000 inhabitants, and 237 have less than 1,000. Additionally, these municipalities exhibit significantly larger areas and lower population densities. Regarding land use, the municipalities where wind farms are developed have lower proportions of artificial surface and agricultural land and higher proportions of bushes or herbaceous vegetation. While a smaller proportion of municipalities affected by a wind farm have an independent party in power, the summary statistics do not indicate substantial differences in the distribution of political power.

[8] Administrative permits for wind farms with an installed power exceeding 50 Megawatts or those that affect the territory of more than one region are granted by the Central Government. Wind farms with installed capacity below 50 Megawatts can be registered as a special category energy producer, entitling them to receive the favorable treatment associated with this category. The current data set does not include any wind farm with an installed capacity above 50 Megawatts.

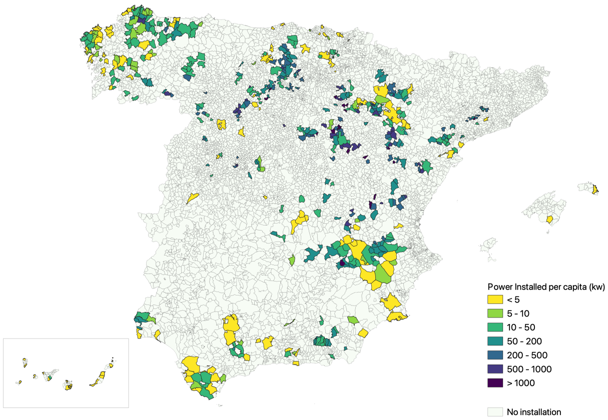
[9] Notice that the data provided by the Spanish Register of Energy Producers facilitates only one municipality name per installation. The current dataset indicates that 505 municipalities are affected by a wind farm. However, this number could be larger if installations affect neighboring municipalities.

Figure 4.1.: Geographical Distribution of Wind Farm Installations

(a) First Year of Installation



(b) Total Power Per Capita (kW)



Notes: Panel (a) shows the first year a wind farm was installed in each affected municipality. Panel (b) reports the wind power per capita installed in each municipality in 2020. Data from the Spanish Registry of Energy Producers (Electra).

4.2.2. Municipal Organization and Tax Instruments

Spain comprises 8,131 municipalities, the basic local entity within the state's organizational structure. The range of basic services that a municipality must provide depends on its population size. While all municipalities are obliged to provide services such as street lighting, waste collection, sewage management, or public road maintenance, the extent of these services increases with the municipality's population.[10] The main sources of municipal financial resources are constituted by

[10]The Law 7/1985 establishes the foundation of the local regime and outlines the responsibilities of municipalities based on their population size. Municipalities with more than 5,000 inhabitants

Table 4.1.: Summary Statistics: Municipal Characteristics

	(a) With Wind Power Plant (N=505)		(b) Without Wind Power Plant (N=7624)			
Municipal Area (km2)	Mean	St. Dev.	Mean	St. Dev.	t-test	(p-value)
Full Sample	129.358	149.220	57.636	85.088	-17.267	0.000
<20,000 inhabitants	111.393	101.938	54.168	70.647	-16.500	0.000
Land Use (%)						
Atrifical Surface	1.110	3.689	2.251	7.169	3.537	0.000
Agricultural land	48.799	27.564	54.858	30.764	4.301	0.000
Forest	17.731	17.150	18.124	20.649	0.417	0.677
Bushes and/or herbaceous	29.665	20.800	22.697	21.233	-7.131	0.000
Open spaces with scarce vegetation	2.342	9.107	1.841	7.936	-1.357	0.175
Wetland	0.248	2.018	0.130	1.489	-1.678	0.093
Water bodies	0.481	1.608	0.472	1.966	-0.094	0.925
Wind potential						
IEC1	30.436	6.808	21.896	6.823	-27.166	0.000
IEC3	37.173	7.543	27.501	7.926	-26.561	0.000
Wind density (100m)	40,840.716	13,511.188	28,634.748	14,271.687	-18.621	0.000
Installed Wind Capacity (kW)						
Total Power (end of period)	52,032.384	52,151.228	-	-	-	-
Total Power (first installation)	31,338.962	27,363.653	-	-	-	-
Power per capita (end of period)	188.267	385.678	-	-	-	-
Power per capita (first installation)	134.989	270.260	-	-	-	-
Demographic						
Population density (full sample)	60.524	265.795	146.083	817.554	2.343	0.019
Population density (<20,000)	28.249	61.753	82.702	465.799	2.533	0.011
Population (full sample)	8,525.685	37,532.297	4,692.330	44,910.925	-1.870	0.062
Population (<20,000)	2,643.415	3,660.046	1,768.766	3088.927	-5.870	0.000
Population younger than 15 (%)	12.113	4.994	11.964	5.231	-0.602	0.547
Population older than 64 (%)	26.136	10.049	26.361	10.773	0.444	0.657
Ideology (% of municipalities)						
Extreme Left	2.020	14.083	2.912	16.815	1.154	0.249
Left	40.404	49.120	38.772	48.726	-0.722	0.471
Center-Left	1.010	10.010	0.459	6.760	-1.697	0.090
Center-Right	13.939	34.671	16.448	37.074	1.464	0.143
Right	35.152	47.793	31.217	46.341	-1.827	0.068
Independent Party	6.263	24.253	9.470	29.282	2.384	0.017

Notes: Summary statistics of municipal characteristics prior to the development of a wind farm. Measures of land use shares, population density, demographic characteristics, and political parties correspond to 1996. Measures of final installed capacity and wind potential correspond to the year 2020.

locally managed tax instruments and inter-governmental grants. Locally managed taxes consist of three direct and two indirect taxes. Direct taxes, which are to be paid annually, are composed of the property tax, serving as one of the main sources of

are obliged to provide public parks, libraries, markets, and waste treatment services. In addition to these provisions, municipalities with over 20,000 inhabitants must also provide civil protection, social services, fire prevention and extinction, sports facilities for public use, and slaughterhouse. Furthermore, municipalities surpassing 50,000 inhabitants are further required to provide urban collective passenger transport and environmental protection services.

municipal revenue, the tax on economic activities, and the tax on motor vehicles. The two indirect taxes managed at the municipal level are composed of the construction and building works tax, as well as the tax on the appreciation of urban land value.[11]

Apart from bi-lateral agreements with developers, municipalities can primarily financially benefit from the development of wind farms in their territory through two direct taxes, the Special Category Property Tax (IBICE) and the Economic Activity Tax (IAE), as well as an indirect tax, the Construction and Building Works Tax (ICIO). Moreover, developers must pay a fee for the granting of urban planning licenses at the time of obtaining the building permit. The national-level regulations governing these tax instruments define their key characteristics, including the tax base, minimum and maximum tax rates, and administrative processes. While municipalities cannot modify the fundamental aspects of each tax instrument, they retain a certain degree of autonomy in setting the tax rates applied within their territory. Table 4.2 provides summary statistics for the tax instruments described below.

Table 4.2.: Municipal Tax Instruments: Tax rates, 2020

	Mean	s.d.	Min	Max
Property Tax				
Rural	0.619	0.197	0.3	1.2
Urban	0.588	0.138	0.3	1.2
Special	0.859	0.329	0.4	1.3
Economic Activity Tax				
Minimum Coefficient	1.119	0.475	0.4	3.8
Maximum Coefficient	1.296	0.719	0.4	3.8
Construction, Installation and Building Works Tax	2.379	1.060	0.0	4.0

Notes: Summary statistics of the main municipal tax instruments and their categories. Data corresponding to the year 2020. The data includes the 7,606 municipalities part of the common tax regime.

Property Tax. The Property Tax is a direct tax on property value to be paid annually. Properties are categorized into three types: rural, urban, and special characteristics. Special characteristics properties include installations related to energy production, dams, roads and highways, ports, and airports. Although the tax base definition, minimum and maximum tax rates are determined at the central level,

[11]Municipal financial resources further comprises revenue generated from the entity's assets, subsidies, public prices, credit operations, fines, and penalties. Additionally, municipalities that are capital or those with more than 75,000 inhabitants can participate in central and regional government taxes. Inter-governmental grants are allocated based on a formula considering population size, with increasing weights applied at thresholds of 5,000, 20,000, and 50,000 inhabitants (Local Treasury Regulatory Law 39/1988 and Royal Legislative Decree 2/2004).

municipalities can set the tax rate for each property category within their jurisdiction.

The tax base for rural and urban properties is based on the cadastral value. However, for properties of special characteristics, the cadastral value considers not only the value of the land but also the value of the installation itself. For this type of property, the tax assessment considers all the elements necessary for their operation, including land, buildings, and installations. After a Supreme Court ruling on the year 2007, wind farms with an installed power of less than 50 megawatts were reclassified and included in the special category of property. This inclusion resulted in a significant increase in the tax base, as the machinery integrated within wind farms began to be considered part of the special characteristics tax base. Urban property can be taxed at rates ranging from 0.3 and 1.10 percent, rural property can be taxed between 0.3 and 0.9 percent, and special characteristics property can be taxed at a rate ranging from 0.4 to 1.3 percent.[12]

Economic Activity Tax. The Economic Activity tax is a direct tax levied on the mere exercise of entrepreneurial, professional, or artistic activities in the municipal territory. For wind farms, the tax rate is determined by the Central Government at 0.721215 euros per generated kilowatt. While local councils do not have the authority to modify the tax rate, they can establish a coefficient scale that considers the physical location of the premises within the municipality. This coefficient, regulated by the municipal by-laws and has to range from 0.4 to 3.8, is applied to the tax liability calculated based on the central government tax rate.

Construction, Installation and Building Works Tax. This tax is levied on every construction project that requires a construction permit within a municipality. The tax is calculated based on the actual and effective cost of the construction, which serves as the tax base. The local council determines the tax rate, ranging from 0 to 4 percent. The payment of this tax is required at the time of obtaining the building permit. Upon completion of the construction, the tax liability is adjusted according to the project's actual cost, and a final settlement is made to reconcile any differences.

4.3. Data

This paper employs a panel dataset at the municipality level covering the period from 1994 to 2020. The dataset combines information on the universe of Spanish

[12]Municipalities have the flexibility to adjust the urban and rural property tax rates beyond the specified ranges if they are a provincial or autonomous community capital, provide public transportation services or more services than legally required, or in the case of having rural land comprising over 80 percent of the total municipal area. When a new cadastral value is established through general collective valuation, the urban and rural tax rates can be reduced to a maximum of 0.1 and 0.075 percent for six years. Additionally, municipalities can introduce a tax credit of up to 90 percent for special characteristics properties.

wind energy installations, along with data on municipal revenue and expenditure, municipal-level tax rates, and sociodemographic characteristics. Table 4.3 provides summary statistics for the main variables of interest, disaggregated by municipalities based on the presence of a wind energy installation.

The Spanish Register of Energy Producers provides information on the municipality name, installed power, and registration date for all wind energy installations across Spain. To construct a comprehensive municipality-level panel dataset representing the evolution of total installed capacity, I aggregate the power installed in each wind farm by municipality and year.[13] I then merge this dataset with data on municipal finances and local tax rates sourced from the Spanish Ministry of Finance.

The Spanish Ministry of Finance provides data on revenue and expenditure at the municipal level starting in 1994. This database contains information on the total budget and the different chapters and sub-chapters categorized within the economic classification. Before 2000, this dataset covers a range of 4,619 to 4,990 out of the 8,122 Spanish municipalities. The coverage expands to include over 8,105 municipalities after 2000. Data on local tax rates covers municipalities part of the common tax regime. Although the data starts from 2000, information on the special characteristics property tax is accessible from 2004 onwards.

Table 4.1 reports summary statistics of municipal geographic and socio-demographic characteristics. I obtain electoral data from the Spanish Ministry of Territorial Policy. I use data from the Spanish National Institute of Statistics (INE) for socio-demographic characteristics. The Global Wind Atlas provides data at a 250 meters grid resolution on the wind speed, wind density, and IEC Capacity Factors. To observe municipality land use, I use data from the CORINE land cover project and aggregate it at the municipal level.

Table 4.3 reports summary statistics of the budget variables and local tax rates for the base year.[14] The primary sources of municipal revenue correspond to current and capital transfers and direct taxes. The most significant categories of expenditure correspond to real investments, current goods and services, and personnel expenses. While, compared to control municipalities, treated municipalities show slightly lower levels of revenue and expenditure per capita, the summary statistics show that significant differences only take place in terms of lower revenue from public prices and fees, as well as lower levels of expenditure in current goods and services and real investment. Regarding local tax rates, treated municipalities report slightly

[13] The Spanish Register of Energy Producers consolidates the registers of each Autonomous Community. One main limitation of the data made public by the Spanish Register appears when cross-checking with the data released by some of the Autonomous Communities. Autonomous Communities data shows that wind farms are likely to affect more than one municipality. Nevertheless, the data released by the Spanish registry only provides one municipality name for each wind farm.

[14] See Appendix A.2 for a brief description of each concept.

Table 4.3.: Summary Statistics: Dependent Variables

	(a) With Wind Power Plant (N=505)		(b) Without Wind Power Plant (N=7624)			
Tax Instruments	Mean	St. Dev.	Mean	St. Dev.	t-test	(p-value)
Property Tax: Rural	0.552	0.190	0.555	0.176	0.392	0.695
Property Tax: Urban	0.509	0.137	0.539	0.154	3.807	0.000
Property Tax: Special	0.699	0.245	0.694	0.234	-0.316	0.752
Economic Activity Tax: Min	0.933	0.177	0.967	0.158	4.199	0.000
Economic Activity Tax: Max	1.052	0.245	1.044	0.224	-0.647	0.517
Construction Tax	1.777	0.946	1.702	0.987	-1.468	0.142
Municipal Budget: Revenue per capita						
Direct Taxes	122.356	112.086	136.133	140.259	1.637	0.102
Indirect Taxes	17.695	31.054	21.676	65.589	1.025	0.306
Public Prices and Fees	82.673	65.714	99.049	129.569	2.131	0.033
Current Transfers	172.267	95.446	174.949	131.534	0.341	0.733
Capital Income	38.553	73.311	48.065	109.730	1.453	0.146
Real Investments	10.710	44.244	12.766	51.680	0.661	0.509
Capital Transfers	140.444	210.872	163.847	291.375	1.343	0.179
Financial Assets and Liabilities	36.006	93.384	31.327	75.210	-1.009	0.313
Total Revenue	620.704	380.769	687.813	494.555	2.265	0.024
Municipal Budget: Expenditure per capita						
Personnel Expenses	136.201	74.021	139.206	92.804	0.540	0.589
Current Goods and Services	159.523	90.291	180.742	123.152	2.880	0.004
Financial	9.034	11.500	8.138	12.538	-1.184	0.236
Current Transfers	31.623	35.880	31.230	47.956	-0.137	0.891
Real Investment	224.512	257.942	268.031	342.157	2.124	0.034
Capital Transfers	12.053	35.003	11.051	37.884	-0.438	0.661
Financial Assets and Liabilities	36.006	93.384	31.327	75.210	-1.009	0.313
Total Expenditure	595.462	351.681	661.584	474.938	2.327	0.020

Notes: Summary statistics for the key variables of interest, distinguishing between treated (Panel a) and control (Panel b) municipalities. The data on municipal revenue and expenditure pertains to the year 1998. Data on local tax rates corresponds to the year 2000, except for the special property tax rate, which is available from 2004. Monetary values are expressed in per capita terms.

lower urban property tax rates and lower minimum economic activity tax coefficient values.[15]

4.4. Empirical Strategy

I employ a difference-in-difference identification strategy to estimate the effect of wind farm installation on municipal revenue, expenditure, and local tax responses.[16] The baseline approach is to estimate a standard difference-in-difference model, where

[15] In Appendix A, Table A.1 reports summary statistics of municipalities divided into terciles of installed wind power. Treated municipalities do not exhibit important differences in either population in terms of municipal revenue.

[16] This methodology has also been used to analyze the local impact of wind farm development by E. Brunner et al. (2022) and E. J. Brunner and Schwegman (2022).

municipalities are considered to be treated when the construction of the first wind farm in their territory begins. Specifically, the model is formulated as follows:

$$Y_{i,t} = \alpha + \beta D_{i,t} + \gamma X_{i,t} + \theta_i + \zeta_t + \varepsilon_{i,t} \tag{4.1}$$

where $Y_{i,t}$ denotes the outcome of interest in municipality i and year t; $D_{i,t}$ is an indicator variable taking the value of one if municipality i had a wind farm installed in year t; $X_{i,t}$ is a vector of controls at the municipality-year level, including land use shares and the political party ideology of the mayor; θ_i and ζ_t denote municipality and year fixed effects, respectively; and $\varepsilon_{i,t}$ is a random disturbance term. Standard errors are clustered at the municipality level to account for the variation in treatment at the municipality-year level. The main coefficient of interest, β, represents the difference-in-difference estimate of the effect of the first wind farm development on the outcome of interest. This estimate is interpreted as the average yearly effect on the outcome of interest from the beginning of the construction phase onward.

To capture the effects occurring during the construction phase, I consider a municipality to be treated three years prior to its preliminary inscription in the Energy Producers Register. The preliminary inscription takes place once the installation is already constructed and serves as a prerequisite to start the testing phase.[17] To control for potential effects from subsequent wind energy installations, I include a control variable representing the cumulative wind power installed in each municipality and year. This variable is defined as the accumulated wind power installed in each municipality and year minus the power installed in the treatment year.[18] The model specification incorporates municipality and year-fixed effects to ensure that the estimates are identified within year and municipality variation in wind farm installation exposure.

To ensure cleaner comparison groups, I implement two sample restrictions. First,

[17] By adopting a three-year pre-treatment assignment, I follow a similar approach to previous studies such as Fabra et al. (2023) and Costa and Veiga (2021). Fabra et al. (2023) consider the construction phase of a wind power plant to take between 20 and 24 months, and Costa and Veiga (2021) consider the construction phase of a wind power plant to take an average of two years. I extend the construction phase one extra year to capture, on the one hand, the effects of installations with longer construction duration and, on the other, potential financial interactions with municipalities taking place before the construction of the wind farm starts. In the Appendix, Figure A.2a shows the distribution of municipalities based on the first year a wind farm started to be constructed in its territory.

[18] In the Appendix A, Figure A.2b illustrates the distribution of treated municipalities based on the share of wind power installed on the first treatment year. This figure shows that treated municipalities are likely to be exposed to multiple wind energy developments over time. Around 40 percent of the municipalities experience additional wind energy developments after the installation of the first wind farm.

I restrict the analysis to municipalities with less than 20,000 inhabitants. Financial resources and spending obligations attributed to municipalities increase with their population size. By excluding larger municipalities, I ensure that the estimated effects are based on a more homogeneous sample of municipalities in terms of spending needs and financial capacities. This restriction results in the exclusion of 44 treated municipalities and 370 controls from the analysis. Second, I exclude control municipalities geographically adjacent to treated municipalities. By doing so, I obtain a cleaner control group and rule out any bias resulting from potential spillover effects. Although the Spanish Register of Energy Producers provides information only for the main municipality where a wind farm is installed, data from autonomous communities indicate that neighboring municipalities are also likely to be affected. After excluding neighboring municipalities, the final sample includes 6,829 municipalities, of which 461 have at least one wind farm within their territory.

To examine the temporal dynamics of the effect and assess the validity of the parallel-trend assumption, I complement the difference-in-difference specification with an event-study model. Estimating an even-study model allows to observe how the effect evolves over time and provides further evidence on the robustness of the difference-in-difference results. Observing the temporal dynamics is especially relevant as the increase in municipal revenue can stem from various sources throughout the lifespan of the wind farm. The model is specified as follows:

$$Y_{i,t} = \beta_0 + \sum_{k=-5}^{k=-1} \beta_k^{lead} D_{i,t}^k + \sum_{k=1}^{k=14} \beta_k^{lag} D_{i,t}^k + \gamma X_{i,t} + \theta_i + \zeta_t + \varepsilon_{i,t} \tag{4.2}$$

where $Y_{i,t}$ corresponds to the outcome of interest in municipality i and year t. The number of years before or after the beginning of the construction phase of a wind farm is represented by $k \in [-5, 14]$. The term $D_{i,t}^k$ is a dummy variable that takes a value of one if municipality i in year t is k periods before or after the installation of the first wind farm. The regression includes municipality, θ_i, and year, ζ_t, fixed effects, and a set of control variables $X_{i,t}$. Standard errors, $\varepsilon_{i,t}$, are clustered at the municipality level.

To capture the effects during the construction phase, $D_{i,t}^1$ equals one three years before the year of preliminary inscription in the energy producers register. The omitted category, $D_{i,t}^0$, represents the year before the construction phase starts. I include indicator variables for the five years before a municipality starts being treated ($D_{i,t}^{-5}$ to $D_{i,t}^{-1}$) and up to 10 years after the wind farms becomes operational ($D_{i,t}^1$ to $D_{i,t}^{14}$). To aggregate effects in periods outside this temporal window, $D_{i,t}^{-5}$ and $D_{i,t}^{14}$ take a value of one for all years that are more than five years before the beginning of the construction phase or 14 years after.

The main coefficients of interest in Equation (4.2) are the set of β_k^{lead} and β_k^{lag}. The estimation of β_k^{lead} helps validate the pre-trends assumption as estimates differences between treated and control municipalities prior to the development of a wind farm. β_k^{lag} estimates the effect of wind energy installations on the outcomes of interest. Estimating these treatment indicators allows the coefficients to evolve over time in a non-parametric way and provides information on the temporal dynamics of the effect. All other terms are defined as in Equation (4.1).

The growing body of literature on two-way fixed effects models with staggered treatment timing points to potential sources of bias in cases of heterogeneous treatment effects (Callaway and Sant'Anna, 2021; De Chaisemartin and D'Haultfoeuille, 2022a; Goodman-Bacon, 2021). A potential source of bias derives from comparisons in which earlier treated units are used as controls for later treated units. To address these concerns, I employ two strategies. First, I exclude from the final sample all municipalities that were treated before 1998. By doing so, I ensure that all treated units are observed at least at the base period, and I eliminate potential bias derived from "always treated" municipalities. Second, I follow the approach of Cengiz et al. (2019) and estimate all my models using stacked regressions where each treated unit is matched to "clean" controls.

More specifically, I create a stacked sample where each municipality is assigned to a specific cohort based on the year a wind farm was first developed. For each cohort, I construct a panel dataset that includes all yearly observations for that cohort of treated municipalities and all control municipalities. I then create the stacked sample by appending all the panels. To ensure that comparisons are made between treated and control units within the same cohort, I interact the year and municipality fixed effects with a cohort indicator. By doing so, I address potential concerns derived from bad controls as I ensure that no comparisons are made across different cohorts of treated municipalities. In Appendix B.1, I show that both the magnitude of the estimated effect and its temporal dynamics remain consistent when using the newly developed difference-in-difference estimators proposed by Callaway and Sant'Anna (2021), De Chaisemartin and D'Haultfoeuille (2022b), and Borusyak et al. (2021).

In the empirical work that follows, I start by analyzing the effect of wind farms on municipal non-financial revenue and expenditure. To identify the specific channels through which wind energy installations affect municipality revenue and the types of expenditure financed by them, I decompose the effects on revenue and expenditure into their respective chapters. To ensure comparability across municipalities of different sizes, I normalize all monetary variables by population.To address potential bias from always-treated units, I exclude the 44 municipalities that received a wind farm before 1998 from the base sample. To analyze local tax responses, I focus on the 7,606 municipalities part of the common tax regime.[19]

4.5. Results

I first present the baseline results, which show the aggregate effect of wind farm development on municipal revenue, expenditure, and local tax responses. These baseline results provide a comprehensive overview of the impact of wind energy installations on receiving municipalities. Next, I decompose the aggregate effect to identify the revenue sources through which the effect takes place and the use that municipalities make of this new revenue source. To do so, I estimate the effect for each revenue and expenditure category. This analysis provides insights into the specific mechanisms driving the aggregate effect.

4.5.1. Aggregate Municipal Revenue and Expenditure

I start the analysis by evaluating the average treatment effect of wind farm development on municipal revenue and expenditure. I estimate Equations (4.1) and (4.2) on the baseline sample of municipalities from 1994 to 2020.Tables 4.4 and 4.5 summarize the results from estimating the difference-in-difference model defined by Equation (4.1). Positive and statistically significant coefficients in Table 4.4 indicate that the first wind farm development led to an average yearly increase in municipal non-financial revenue of 274.2 euros per capita. Results in Table 4.5 indicate that municipalities used this new revenue to increase non-financial expenditure by 123.5 euros per capita.

To isolate the monetary effect from population changes, I keep population constant at the beginning of the period. In Tables 4.4 and 4.5, Panel (a) summarizes the results for the specification in which the dependent variable is expressed in per capita terms based on each municipality-year population. Panel (b) reports the results for the specification in which the population is kept constant in 1994. The magnitude of the effect is substantially lower when the monetary effect is isolated from population changes. This difference in magnitude indicates different population dynamics in affected municipalities. Appendix A.4 shows that treated municipalities follow decreasing population trends.

The estimated effect and its magnitude are consistent with the inclusion of controls and the restriction of the sample to more comparable municipalities. Column (1) reports the point estimates for the base specification, including municipality-cohort

[19] Appendix B.3 shows that results are robust regardless of including non-common tax regime municipalities.

Table 4.4.: Effect of Wind Farm Development on Non-financial Revenue (euros per capita)

	(1)	(2)	(3)	(4)	(5)
(a) Observed Population					
First Installation	423.900***	407.500***	348.900***	402.600***	409.500***
	(58.030)	(57.710)	(56.710)	(61.370)	(61.390)
Mean (treated=1, t=0)	875.830	875.867	875.867	882.772	882.956
R-squared	0.203	0.207	0.207	0.207	0.208
(b) Constant Population					
First Installation	248.100***	270.500***	239.300***	276.900***	274.200***
	(57.520)	(57.780)	(58.800)	(64.500)	(64.510)
Mean (treated=1, t=0)	915.462	915.504	915.504	916.826	924.494
R-squared	0.127	0.132	0.132	0.128	0.123
N Municipalities	8,040	8,040	8,040	7,761	6,865
RFE and TFE	Yes	Yes	Yes	Yes	Yes
Mun Charact	No	Yes	Yes	Yes	Yes
Installed Power	No	No	Yes	Yes	Yes
Excluded Municipalities	No	No	No	>20,000	>20,000
Excluded Neighbors	No	No	No	Yes	Yes

Notes: Results from estimating the difference-in-difference model described by Equation (4.1) where the dependent variable is municipal non-financial revenue in euros per capita. Per capita values in terms of observed population (Panel a) and 1994 population (Panel b). Mean indicates the mean value of the outcome variable for treated municipalities before a wind farm has been developed. Controls for municipal characteristics include land use shares and the ideology of the mayor's political party. "Installed power" controls for subsequent wind power installations accumulated at the municipality-year level. The first treatment year is set at three years before the preliminary registration date. Standard errors are clustered at the municipality-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and year-cohort fixed effects. Column (2) includes as controls for municipality-year characteristics the share of land uses and the ideology of the political party to which the mayor belongs. Adding the mayors' ideology as a control helps to isolate confounding effects derived from differences in policies depending on the political alignment of the city council. Column (3) includes as control the accumulated amount of wind power installed in each municipality in subsequent years after the first wind farm development. By controlling for further wind power installations, I isolate potential confounding effects from subsequent developments and provide a more precise identification of the impact of the first wind farm installation.

Columns (4) and (5) restrict the sample to small and non-neighboring municipalities to eliminate bias driven by larger municipalities and potentially affected control units. Column (4) summarizes the results for the sample restricted to municipalities of less than 20,000 inhabitants. Column (5), the preferred specification, excludes non-treated neighboring municipalities from the sample. By limiting the analysis to smaller municipalities and excluding neighboring units from the regression, this specification eliminates potential attenuation biases derived from the introduction of treated units as controls.

The results presented in Table 4.4 suggest that the development of wind farms has a significant positive impact on municipal resources. Specifically, I focus on non-financial revenue as financial revenue is expected to remain unaffected by wind farms.[20] The estimates in Panel (a) indicate an increase in non-financial revenue of 409.5 euros per capita, representing a 46 percent increase relative to the mean value of treated municipalities before the beginning of the construction phase. However, the results in Panel (b) suggest that a portion of this effect can be attributed to population changes. When the population is held constant at the beginning of the analysis period, the increase in non-financial revenue is estimated to be 274.2 euros per capita, representing a 29.7 percent increase compared to the pre-treatment period.

Table 4.5.: Effect of Wind Farm Development on Non-financial Expenditure (euros per capita)

	(1)	(2)	(3)	(4)	(5)
(a) Observed Population					
First Installation	250.600***	236.000***	191.900***	229.300***	235.700***
	(42.110)	(41.820)	(41.490)	(44.610)	(44.620)
Mean (treated=1, t=0)	850.754	850.811	850.811	857.637	857.977
R-squared	0.222	0.226	0.226	0.226	0.226
(b) Constant Population					
First Installation	103.800***	124.200***	99.960***	126.000***	123.500***
	(36.520)	(36.700)	(36.990)	(40.280)	(40.290)
Mean (treated=1, t=0)	887.629	887.686	887.686	889.037	896.283
R-squared	0.166	0.172	0.172	0.169	0.164
N municipalities	8,040	8,040	8,040	7,761	6,865
RFE and TFE	Yes	Yes	Yes	Yes	Yes
Mun Charact	No	Yes	Yes	Yes	Yes
Installed Power	No	No	Yes	Yes	Yes
Excluded Municipalities	No	No	No	>20,000	>20,000
Excluded Neighbors	No	No	No	No	Yes

Notes: Results from estimating the difference-in-difference model described by Equation (4.1) where the dependent variable is municipal non-financial expenditure in euros per capita. Per capita values in terms of observed population (Panel a) and 1994 population (Panel b). Mean indicates the mean value of the outcome variable for treated municipalities before a wind farm has been developed. Controls for municipal characteristics include land use shares and the ideology of the mayor's political party. "Installed power" controls for subsequent wind power installations accumulated at the municipality-year level. The first treatment year is set at three years before the preliminary registration date. Standard errors are clustered at the municipality-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[20] Appendix B.2 shows that these results are consistent to the inclusion of financial revenue.

Results in Table 4.5 indicate that municipalities use the extra revenue generated by wind farms to increase municipal expenditure. However, the magnitude of the effect is smaller than the effect on revenue.[21] Consistent with the findings on revenue, the effect on expenditure is attenuated when population is held constant at the beginning of the period of analysis. In the preferred specification, presented in Column (5) of Panel (b), results indicate that municipalities increase non-financial expenditure by 123.5 euros per capita, representing a 13.8 percent increase relative to the mean expenditure per capita in the pre-treatment period.[22]

After quantifying the aggregate effect on non-financial revenue and expenditure, Figure 4.2 plots the β_k coefficients and associated 95 percent confidence intervals from estimating the event study model defined by Equation (4.2). These results correspond to the specification which includes municipality-cohort and year-cohort fixed effects, controls for municipal characteristics and subsequent wind power installations, and uses the sample restricted to municipalities of less than 20,000 inhabitants not neighboring affected units. β_k^{lead} coefficients close to zero and non-statistically significant show no evidence of a pre-trend in municipal revenue (triangular coefficients in red) or expenditure (rhombus-shaped coefficients in blue).

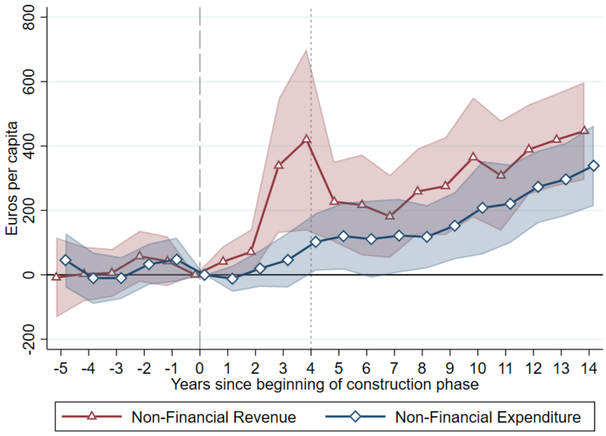
In Figure 4.2, the estimated β_k^{lead} coefficients describe the temporal dynamics of the effect. Positive and statistically significant coefficients indicate an increase in the outcome of interest, k periods after the beginning of the construction phase, relative to the base period $t = 0$. The triangular coefficients in red correspond to the estimated effect on municipal non-financial revenue. These results indicate that wind farm development significantly and consistently impacts municipal non-financial revenue. This effect is substantial during the construction phase. After the construction phase, the increase in revenue slightly decreases in magnitude, and it gradually increases again during the wind farm's lifetime. The rhombus-shaped coefficients correspond to the estimated effect on municipal non-financial expenditure. The effect for municipal expenditure follows an increasing trend and shows a smoother evolution than in the case of revenue. These results indicate that, on average, the increase in municipal expenditure is lower than the increase in revenue. However, the point estimates are not statistically different, and both variables follow a similar trend over time. These results indicate that extra resources generated by wind farms translate into a sustained increase in municipal expenditure.[23]

[21]The Organic Law on Budgetary Stability and Financial Sustainability approved in 2012 limits the spending of public administrations with three financial rules: budget stability, public debt, and expenditure rule. The expenditure rule prevents the spending of public administrations from exceeding the medium-term GDP growth rate of the Spanish economy.

[22]Appendix B.2 shows that these results are consistent with the specification including financial expenditure.

[23]In Appendix B.1, Figure B.2 shows that these results are consistent to alternative difference-

Figure 4.2.: Dynamic Effect of Wind Farm Development on Municipal Finances: Non-financial Revenue and Expenditure (euros per capita)



Notes: Results from estimating the event study model defined by Equation (4.2). The dependent variables are municipal non-financial revenue (coefficients in red represented by a triangle) and non-financial expenditure (coefficients in blue represented by a rhombus). The magnitudes are expressed in euros per capita relative to the 1994 population. These results correspond to the specification including municipality-cohort and year-cohort fixed effects, controls for municipal characteristics, and subsequent wind power installations. The sample is restricted to municipalities of less than 20,000 inhabitants not neighboring affected units. The reference year (represented by the dashed line) is set at the year before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary register to the energy producers register (dotted line). Standard errors are clustered at the municipality-cohort level. Confidence intervals at the 95 percent level.

4.5.2. Local Tax Responses

I study local tax responses to wind farm development by analyzing changes in the different categories of property tax. The results reported in Table 4.6 and Figure 4.3 show that municipalities react to the development of wind farms by increasing tax rates associated with this type of infrastructure while decreasing the fiscal pressure associated with urban and rural land. These results indicate that the increase in municipal revenue derived from wind energy development is not a mechanical effect driven by a broadening of the tax base. The broadening of the tax base is complemented by municipal responses in the form of increases in tax rates associated with this type of non-mobile capital investment close to maximum levels.

The results reported in this section correspond to the sub-sample of municipalities part of the common tax regime.[24] The sample of municipalities that can be analyzed is limited by the data provided by the Spanish Tax Agency. This data contains information on municipal tax rates starting in year 2000 for the urban in rural property tax rates and in year 2004 for the special characteristics tax rate. To prevent

in-difference estimators. Appendix B.2 shows that the results are consistent and stable to including financial information.

[24]The regions of Euskadi and Navarra are not part of this analysis as they belong to a special tax regime and municipalities are subject to different tax regulations. The data provided by the Spanish Tax Agency only contains information for municipalities belonging to the common tax regime.

bias in the results from including always treated units in the analysis, the results presented in this section exclude municipalities that received a wind farm before the beginning of the analysis period. The results from the analysis of urban and rural tax rates is based on the sample of municipalities that received the first wind farm starting in 2004. The results from the special tax rate are based on the sample restricted to municipalities that received the first wind farm starting in 2008.[25]

Table 4.6 summarizes the results from estimating Equation (4.1) on the tax rate logarithm of each category of property tax. Panel (a) summarizes the results of the special tax rate. The results reported in Column (5) indicate that, in aggregate terms, municipalities react to the development of the first wind farm in their territory by increasing by 20 percent the tax rates targeted to them. Panels (b) and (c) report the urban and rustic tax rate results. These results show that local tax responses not only occur by substantially increasing the tax burden of wind farms but are complemented by decreasing the fiscal pressure associated with the other tax categories. Specifically, the results reported in Column (5) indicate that, after the development of the first wind farm, municipalities reduce the urban property tax rate by 2.3 percent (Panel b) and the rural property tax rate by 3.9 percent (Panel c). These results are consistent with the different specifications adding regional and time-fixed effects (Column 1); controlling for municipal characteristics (Column 2); controlling for further wind power installations (Column 3); and restricting the sample to municipalities of less than 20,000 inhabitants (Column 4) and control units not bordering treated municipalities (Column 5).

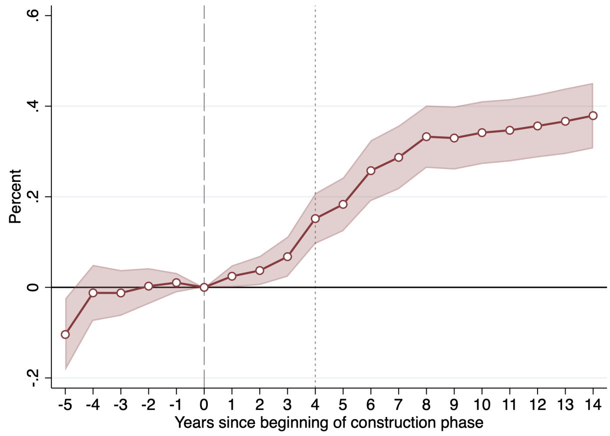
Figure 4.3 plots the β_k coefficients of estimating Equation (4.2) for each of the three property tax categories. Panel (a) shows the results corresponding to the special category property tax. Starting at the construction phase, municipalities react to the construction of a wind farm by progressively increasing the fiscal pressure on this type of investment. The special characteristic tax rate increase stabilizes four years after the wind farm becomes operative when it is set close to maximum levels.[26]

[25] In 2007, a Supreme Court ruling included the machinery used for producing electric energy as part of the special category property tax base. By restricting the sample of treated municipalities to those who received the first wind farm starting in 2008, I further ensure that reactions to this tax base expansion are not driving results. This restriction reduces the number of treated municipalities from 463 to 247 in the case of the urban and rural tax rates, and to 155 in the case of the special category tax rate. Appendix B.3 shows that the results are not significantly different when the analysis is restricted to municipalities that received the first wind farm starting in 2008. Table B.3 shows the difference-in-difference results for non-financial revenue and expenditure. Table B.4 shows the difference-in-difference results for the urban and rural tax rates. Figure B.4 shows the event study results for non-financial revenue (Panel a) and non-financial expenditure (Panel b). Figure B.5 shows the results for the urban (Panel a) and rural (Panel b) tax rates.

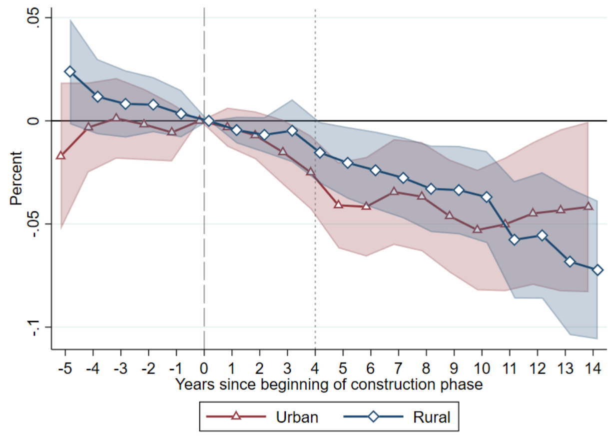
[26] In Appendix A.3, Figure A.3c plots the temporal evolution of the special characteristics tax rate for treated and control municipalities. This figure shows that treated municipalities react to the development of a wind farm by increasing the fiscal pressure on this type of investment close to

Figure 4.3.: Dynamic Local Tax Responses to Wind Farm Development: Property Tax Rates

(a) Special Category Property Tax



(b) Urban and Rural Property Tax



Notes: Results from estimating the event study model defined by Equation (4.2). The dependent variables are the logarithm of the special property tax rate (Panel a), the logarithm of the urban tax rate (red coefficients represented by a triangle in Panel (b), and the rural property tax rate (blue coefficients represented by a rhombus in Panel (b). Results correspond to the specification, including municipality-cohort and year-cohort fixed effects, controls for municipal characteristics, and subsequent wind power installations. Results in Panel (a) correspond to the sample of municipalities of less than 20,000 inhabitants not neighboring affected units part of the common tax regime that received the first wind farm installation after 2008. Results in Panel (a) correspond to the sample of municipalities of less than 20,000 inhabitants not neighboring affected units part of the common tax regime that received the first wind farm installation after 2004. The reference year (represented by the dashed line) is set at the year before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary energy producers register (dotted line). Standard errors are clustered at the municipality-cohort level. Confidence intervals at the 95 percent level.

Table 4.6.: Local Tax Responses to Wind Farm Development: Property Tax Rates

	(1)	(2)	(3)	(4)	(5)
(a) Special Property Tax					
First Installation	0.206***	0.207***	0.189***	0.194***	0.201***
	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)
Mean (treated=1, t=0)	0.786	0.786	0.786	0.773	0.773
R-squared	0.123	0.124	0.124	0.120	0.111
Municipalities	7,281	7,281	7,281	6,995	6,142
(b) Urban Property Tax					
First Installation	-0.034***	-0.037***	-0.031***	-0.024**	-0.023**
	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
Mean (treated=1, t=0)	0.607	0.607	0.607	0.606	0.606
R-squared	0.133	0.139	0.139	0.148	0.146
Municipalities	7,362	7,362	7,362	7,096	6,238
(c) Rural Property Tax					
First Installation	-0.034***	-0.035***	-0.035***	-0.038***	-0.039***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Mean (treated=1, t=0)	0.592	0.595	0.595	0.587	0.587
R-squared	0.103	0.104	0.104	0.107	0.108
Municipalities	7,362	7,362	7,362	7,095	6,237
RFE and TFE	Yes	Yes	Yes	Yes	Yes
Mun Charact	No	Yes	Yes	Yes	Yes
Installed Power	No	No	Yes	Yes	Yes
Excluded Municipalities	No	No	No	>20,000	>20,000
Excluded Neighbors	No	No	No	No	Yes

Notes: Results from estimating the difference-in-difference model described by Equation (4.1). The dependent variables are the logarithm of the special property tax rate (Panel a), the logarithm of the urban property tax rate (Panel b), and the logarithm of the rural property tax rate (Panel c). Mean indicates the mean value of the outcome variable for treated municipalities in the period before the development of a wind farm. Controls for municipal characteristics include land use shares and the ideology of the mayor's political party. "Installed power" controls for subsequent wind power installations accumulated at the municipality-year level. The first treatment year is set at three years before the preliminary registration date. Standard errors are clustered at the municipality-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results show no evidence of pre-trends as coefficients prior to the beginning of the construction phase are non-significant and close to zero.

Results reported in Figure 4.3b show that, while municipalities react to the development of a wind farm by increasing tax rates targeted to them, they decrease the fiscal pressure associated with the rest of the property tax categories. Although the temporal dynamic is the same for all three categories, the decrease in tax rates associated with urban and rural land is significantly smaller. In the case of the urban property tax, the largest decrease takes place at the beginning of the construction

maximum levels.

phase and stabilizes once the wind farm becomes operative. Turning to the fiscal pressure associated with rural land, results show a progressive decrease in its fiscal pressure. Non-statistically significant coefficients close to zero prior to the beginning of the construction phase show no evidence of pre-trends.[27]

4.5.3. Identification of Revenue Sources

I decompose the aggregate revenue effect into the different revenue sources to identify the main channels through which wind farms affect municipal resources.[28] In addition to the local tax responses documented above, the development of a wind farm is expected to increase revenue generated from direct and indirect taxes as it mechanically increases its tax bases. Furthermore, municipalities can increase their capital income through royalty payments or property rents. Table 4.7 summarizes the results from estimating the difference-in-difference model defined by Equation (4.1) for each revenue chapter. These results show that the most significant increase in municipal revenue occurs through an increase in revenue generated from indirect taxes (i.e., the construction tax), followed by an increase in revenue generated from capital income and direct taxes (i.e., property tax and economic activity tax).

More specifically, Table 4.7 shows that increases in capital income explain 20 percent of the increase in municipal revenue. The remaining revenue effect corresponds to increases in revenue generated from direct and indirect taxes. Columns (1), (2), and (5) show that a wind farm development increases the revenue generated from direct taxes by 52 percent, doubles capital income, and multiples by three the revenue generated from the construction tax. The increase in capital income, which includes concepts such as income from rents, concessions, and special uses or dividends and profit shares, is especially relevant in this contest as it represents another form through which municipalities benefit from the development of a wind farm beyond the mechanical increase due to expansions in the tax base.[29]

[27] In Appendix A.3, Figures A.3a and B.1c plot the temporal evolution of the urban and rural tax rates in treated and control municipalities. This figure shows that, although the magnitude of the change in trends is small, treated municipalities exhibit a decrease in tax rates associated with urban and rural property once a wind farm is built in their territory.

[28] See Appendix A.2 for the definition of each revenue chapter.

[29] Municipalities of less than a thousand inhabitants are only obliged to report budget information disaggregated at the chapter level. At this level of aggregation, this analysis cannot identify the specific sources through which the increase in capital income takes place.

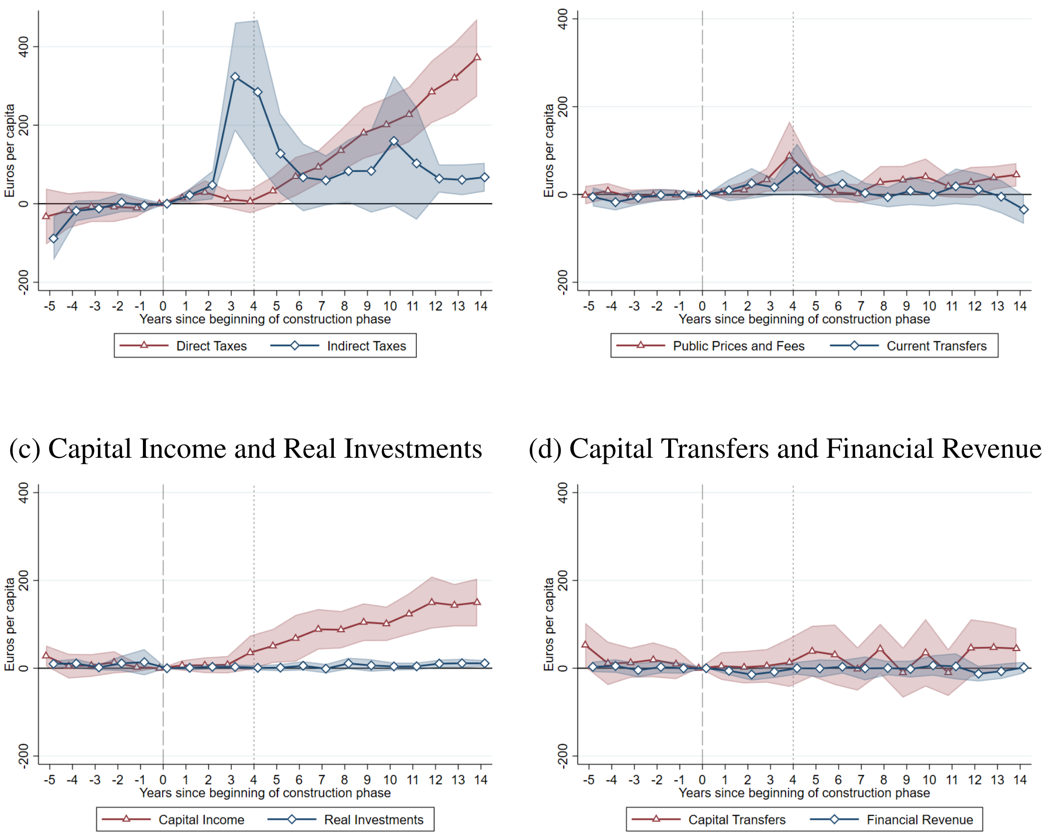
Table 4.7.: Effect of Wind Farm Development on Municipal Revenue: Decomposition by Revenue Source

	(1) Direct Taxes	(2) Indirect Taxes	(3) Public Prices and Fees	(4) Current Transfers	(5) Capital Income	(6) Real Investments	(7) Capital Transfers	(8) Financial Assets	(9) Financial Liabilities
First Installation	98.030***	135.300***	14.000	-18.180*	57.040***	-4.381	-7.599	0.397	-7.735***
	(30.210)	(42.580)	(8.756)	(10.300)	(10.850)	(4.635)	(13.450)	(0.343)	(2.524)
Mean (treated=1, t=0)	185.450	34.742	140.688	242.171	56.510	24.163	240.770	1.540	37.253
N municipalities	6,865	6,865	6,865	6,865	6,865	6,865	6,865	6,865	6,865
R-squared	0.154	0.009	0.031	0.199	0.016	0.002	0.062	0.000	0.018
RFE and TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mun Charact	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Installed Power	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded Municipalities	>20,000	>20,000	>20,000	>20,000	>20,000	>20,000	>20,000	>20,000	>20,000
Excluded Neighbors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Results from estimating the difference-in-difference model described by Equation (4.1). The dependent variables are each revenue source expressed in euros per capita relative to 1994 population. Mean indicates the mean value of the outcome variable for treated municipalities in the period of time before the development of a wind farm. Controls for municipal characteristics include land use shares and the ideology of the mayor's political party. "Installed power" controls for subsequent wind power installations accumulated at the municipality-year level. The first treatment year is set at the beginning of the construction phase. The construction phase is considered to start three years before the preliminary registration date. Standard errors are clustered at the municipality-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 4.7, Columns (8) and (9) analyze changes in municipalities' financial behavior. Negative coefficients associated with financial liabilities (i.e., loans and credits) show that municipalities react to wind farm development by decreasing their indebtedness. Column (4) shows that resources derived from current transfers slightly decrease after the first wind farm. This exercise further provides evidence of the validity of the results by showing null impacts on the revenue sources not expected to be affected by wind energy installations.

Figure 4.4.: Dynamic Effect of Wind Farms Development on Municipal Revenue: Decomposition by Revenue Category



(a) Direct and Indirect Taxes

(b) Public Prices and Current Transfers

(c) Capital Income and Real Investments

(d) Capital Transfers and Financial Revenue

Notes: Results from estimating the event study model defined by Equation (4.2). The dependent variables are municipal revenue in euros per capita from direct taxes and indirect taxes (Panel a); public prices and current transfers (Panel b); capital income and real investments (Panel c); and capital transfers and financial revenue (Panel d). Per capita measures in terms of 1994 population. Results correspond to the specification reported in Table 4.7 which includes municipality-cohort and year-cohort fixed effects, controls for municipality characteristics and subsequent wind power installations, and restricts the sample to municipalities of less than 20,000 inhabitants not bordering treated units. The reference year (dashed line) is set a the year before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary register to the energy producers register (dotted line). Standard errors are clustered at the municipality-cohort level. Confidence intervals are shown at the 95 percent level.

To document the temporal evolution of the estimated effect and evaluate the existence of pre-trends, Figure 4.4 plots the β_k's and associated 95 percent confidence intervals from estimating Equation (4.2). These results show no evidence of pre-trends and indicate that the channels through which wind farm development increases municipal resources change along the lifetime of the infrastructure. Panel (a) shows the point estimates for Direct (triangles) and Indirect (rhombus) taxes. These results indicate that during the construction phase the increase in resources is generated through an expansion in the revenue generated from indirect taxes. Yet, once the operation phase starts, the effect on indirect taxes decreases and is compensated by an increase in resources generated from direct taxes and capital income (Panel c). The null impact on the remaining categories further validates the robustness of this analysis.

4.5.4. Decomposition of the Effect on Expenditure

I decompose the increase in expenditure into each of its categories to better understand the use that municipalities make of the extra revenue generated from wind farms.[30] Table 4.8 summarizes the results from estimating the difference-in-difference model defined by Equation (4.2). These results indicate that municipalities mainly use these new resources to finance increases in current expenditures and real investments. Municipality's current expenditure is primarily utilized to finance its day-to-day activity, encompassing a range of expenses such as supplies, purchases or services rendered. On the other hand, real investment refers to expenses that are typically more visible in nature and are aimed at increasing the provision of long-lasting public investments within the municipality.

More specifically, Table 4.8 shows that 72 percent of the resources allocated to increase municipal expenditure are directed towards real investments. Compared to the use of resources that municipalities made before the development of a wind farm, Column (2) indicates that municipalities increased current expenditure by 10 percent, and real investments by 24 percent (Column 5). The substantial increase in real investments can be interpreted as a form of indirect compensation to hosting communities with the revenue generated from wind farms. I complement this analysis by estimating the effect on expenditure associated with financial assets (Column 7) and liabilities (Column 8). Negative coefficients associated with financial liabilities indicate a decrease in financial resources allocated towards paying off public debt, suggesting that municipalities used this new financial resource to decrease their debt burden.

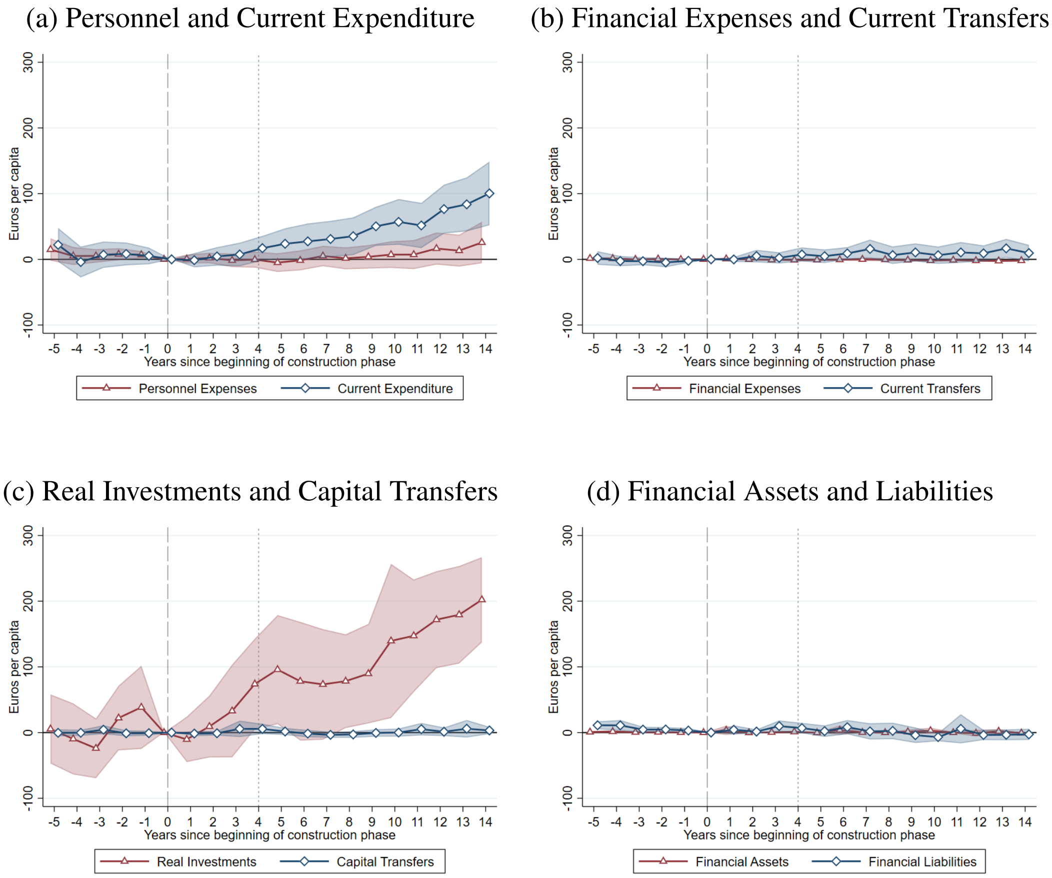
[30] See Appendix A.2 for the definition of each expenditure chapter.

Table 4.8.: Effect of Wind Farm Development of Municipal Expenditure: Decomposition by Expenditure Category

	(1) Personnel Expenses	(2) Current Expenditures	(3) Financial Expenses	(4) Current Transfers	(5) Real Investments	(6) Capital Transfers	(7) Financial Assets	(8) Financial Liabilities
First Installation	-3.364	29.040**	-1.642***	8.416	89.640***	1.435	0.345	-4.784**
	(8.325)	(12.99)	(0.555)	(5.556)	(21.590)	(2.272)	(0.532)	(2.142)
Mean	197.759	267.096	8.644	43.276	369.254	10.254	1.537	25.496
N (municipalities)	6,865	6,865	6,865	6,865	6,865	6,865	6,865	6,865
R-squared	0.261	0.202	0.026	0.042	0.068	0.003	0.000	0.017
RFE and TFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mun Charact	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Installed Power	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excluded Municipalities	>20,000	>20,000	>20,000	>20,000	>20,000	>20,000	>20,000	>20,000
Excluded Neighbors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Results from estimating the difference-in-difference model described by Equation (4.1). The dependent variables are each category of expenditure expressed in euros per capita relative to the 1994 population. Mean indicates the mean value of the outcome variable for treated municipalities in the period before the development of a wind farm. Controls for municipal characteristics include land use shares and the ideology of the mayor's political party. "Installed power" controls for subsequent wind power installations accumulated at the municipality-year level. The reference period (dashed line) is set at the year before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary register to the energy producers register. Standard errors are clustered at the municipality-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4.5.: Dynamic Effect of Wind Farm Development on Municipal Expenditure: Decomposition by Expenditure Category



Notes: Results from estimating the event study model defined by Equation (4.2). The dependent variables are personnel and current expenditures (Panel a); financial expenditure and current transfers (Panel b); real investments and capital transfers (Panel c); and financial assets and liabilities (Panel d). Magnitudes are expressed in per capita terms relative to the 1994 population. The results correspond to the specification which includes municipality-cohort and year-cohort fixed effects, controls for municipality characteristics and subsequent wind power installations, and restricts the sample to municipalities of less than 20,000 inhabitants not bordering treated units. Reference year (represented by the dashed line) is set at the beginning of the construction phase. The construction phase is considered to start three years before the preliminary inscription to the energy producers register (dotted line). Standard errors are clustered at the municipality-cohort level. Confidence intervals are shown at the 95 percent level.

Figure 4.5 plots the β_k coefficients and associated 95 percent confidence intervals from estimating Equation (4.2) for each category of expenditure. The results show no evidence of pre-trends as point estimates before the development of a wind farm are close to zero and statistically insignificant. The increase in expenditure follows a smoother upward trend compared to municipal revenue, with increases becoming more prominent during the operation phase. Coefficients corresponding to real investments (Panel c) are less precisely estimated. Yet treated municipalities still demonstrate a significant increase in the allocation of resources towards funding public investment. Small and statistically insignificant coefficients associated with the remaining expenditure categories further demonstrate the robustness of the results and prove that they do not stem from identifying a systematic change.

4.6. Concluding Remarks

Understanding whether local communities benefit from the development of wind farms in their territory is a necessary step to design and implement, if needed, compensation mechanisms aiming at mitigating the local costs associated to the energy transition and improve the efficiency in the development of renewable energies. This paper contributes to this debate by clearly identifying the effect of wind farm development on municipal finances and local tax responses. To do so, I combine data on the development of wind farms in Spain with a panel dataset on municipal budgets and tax rates from 1994 and 2020. To causally identify the effect of a wind farm, I use difference-in-differences and event-study methodologies, which exploit spatial and temporal variation of their development.

The results show that, at mean levels, the development of a wind farm has a long-lasting positive effect on municipal revenue per capita. This effect is partially driven by an expansion of the tax base and complemented by local tax responses in the form of increases close to the maximum tax rates associated with this type of infrastructure. By decomposing the effect on revenue into its different categories, I show that the channels through which municipalities benefit from their development change along the lifetime of the infrastructure. Although during the construction phase, the increase in revenue occurs through a larger yield from indirect taxes, the long-lasting effect on municipal revenue is generated by increased capital income and direct taxes. The increase in property tax rates associated with wind farms indicate that the effect on revenue generated from direct taxes is not only driven by expansions of the tax base but complemented by local reactions aimed at maximizing the revenue generated from this type of infrastructure.

After quantifying the revenue effect, I analyze whether municipalities use these new resources to indirectly compensate the local community. I find that the revenue generated by wind farms is channeled toward increases in current expenses and real investment. The largest share of the newly generated income is allocated to real investments indicating that municipalities use the revenue generated by wind farms to indirectly compensate hosting communities by increasing investment in infrastructure and durable goods. The increase in expenditure is complemented by decreases in fiscal pressure associated with urban and rural property.

This study makes several contributions. First, I add to the literature analyzing the local impact of renewable energy projects by examining the nationwide effects of wind farm development on municipal financial resources in a context in which specific compensation mechanisms are absent. Second, I contribute to the literature analyzing reactions to large capital-intensive projects through local taxation responses. The results shown in this paper provide evidence that hosting municipalities increase tax rates levied on wind farms close to the maximum level while decreasing fiscal pressure associated with other tax categories. Last, the literature analyzing the effect of natural resource windfalls has mainly focused on the impact of shale oil and gas booms. This paper adds to this body of literature by analyzing the effect of wind exploitation, a natural resource with substantially different effects in terms of local employment and project durability.

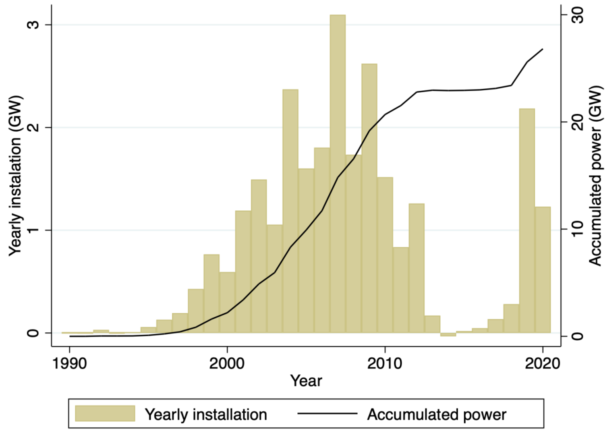
The conclusions that derive from this analysis point to important avenues for future research. First, exploring differences in the use of financial resources and local tax responses based on the ideology of municipalities' city councils can bring further insight into the political economy behind the development of renewable energies. Second, the use of municipalities' financial resources is limited by their competencies. Exploring whether opposition to wind farm development reacts differently to implementing more direct compensation mechanisms, such as in-kind transfers, subsidized access to electricity, or wind farm ownership, could help design tools to mitigate the locally-concentrated negative externalities associated with this type of infrastructure. Last, the visual and noise impacts of wind farms extend beyond the geographical territory of a municipality. If the revenue shock is concentrated in the municipality where a wind farm is developed, opposition from neighboring municipalities is likely to rise. Thus, understanding whether opposition to wind farm development varies depending on the financial impact of the infrastructure in the municipality could help implement mechanisms mitigating negative externalities and opposition in neighboring municipalities.

The results of this analysis have important policy implications. Although they show that municipalities financially benefit from the development of wind farms in their territory, local opposition to new developments is still present. If opposition stands from a lack of information of the financial impact of this type of infrastructure, promoting the transfer of information to local residents could help mitigate local objections. The results presented in this paper point to the need to design comprehensive mechanisms helping to compensate for local costs, mitigate local objections, and minimize conflicts around planned investments to move toward a more efficient and socially inclusive energy transition.

A. Additional Material

A.1. Supplementary Descriptive Information

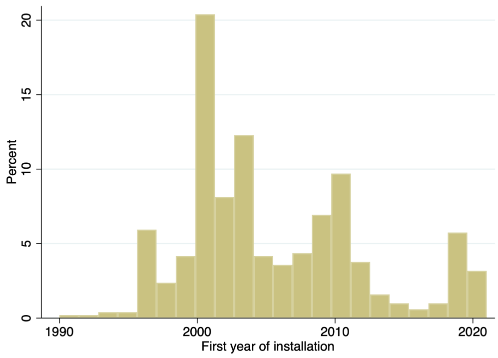
Figure A.1.: Evolution of Installed Wind Power at the National Level (Spain)



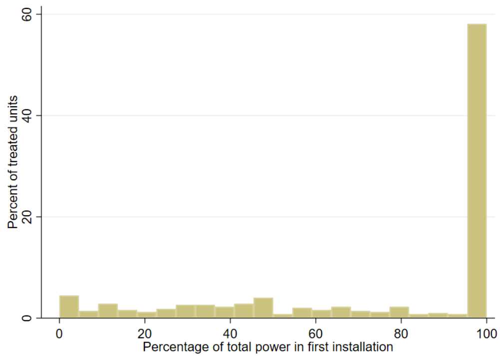
Notes: Evolution of wind power installation in Spain from 1990 to 2020. Bars correspond to the left y-axis and represent yearly installations measured in Gigawatts. The line corresponds to the right y-axis and represents yearly accumulated wind power measured in Gigawatts. Data from Eurostat.

Figure A.2.: Distribution of Treated Municipalities

(a) First Year of Development



(b) Share of Total Power in First Development



Notes: Panel (a) shows the distribution of municipalities based on the first year a wind farm started to be constructed in each treated municipality. Panel (b) shows the distribution of municipalities based on the share of power installed in the first treatment year over the total power installed at the end of the analysis period. Municipalities correspond to the baseline sample and exclude municipalities with more than 20,000 inhabitants. Roughly 60 percent of municipalities had the total wind capacity in their territory installed in the first year a wind power plant was developed. The remaining 40 percent of municipalities had further wind power installations after the first development in their territory.

Table A.1.: Summary statistics: Municipalities Categorized in Terciles of Installed Wind Power

	Tercile								
	Lower			Middle			Higher		
	Mean (Sd)	Min	Max	Mean (Sd)	Min	Max	Mean (Sd)	Min	Max
Inicial Pw (kW)	6,671.312 (5,944.615)	0	17,560	27,144.623 (5,507.257)	17,850	36,550	61,192.329 (26,726.952)	36,630	198,055
Inicial Pw Pc (kW)	39.263 (105.110)	0.00	733.33	113.921 (174.728)	1.03	1,050.00	277.139 (398.721)	2.27	2,083.33
Population	3,298.384 (4,001.791)	26	19,367	2,381.785 (3,379.187)	14	17,306	1,878.494 (2,976.851)	36	16,891
Total Revenue (pc94)	595.042 (361.262)	168.087	2,373.442	624.936 (503.776)	179.853	3,339.773	544.606 (271.179)	205.230	2,038.116

Notes: Summary statistics by terciles of municipalities defined in terms of total power installed in the first wind farm development in their territory. Population and municipal revenue correspond to values prior to the development of a wind farm. Municipal revenue expressed in per capita values relative to 1994 population.

A.2. Budget Decomposition: Chapters Definition

Municipal revenue is composed of the following chapters:

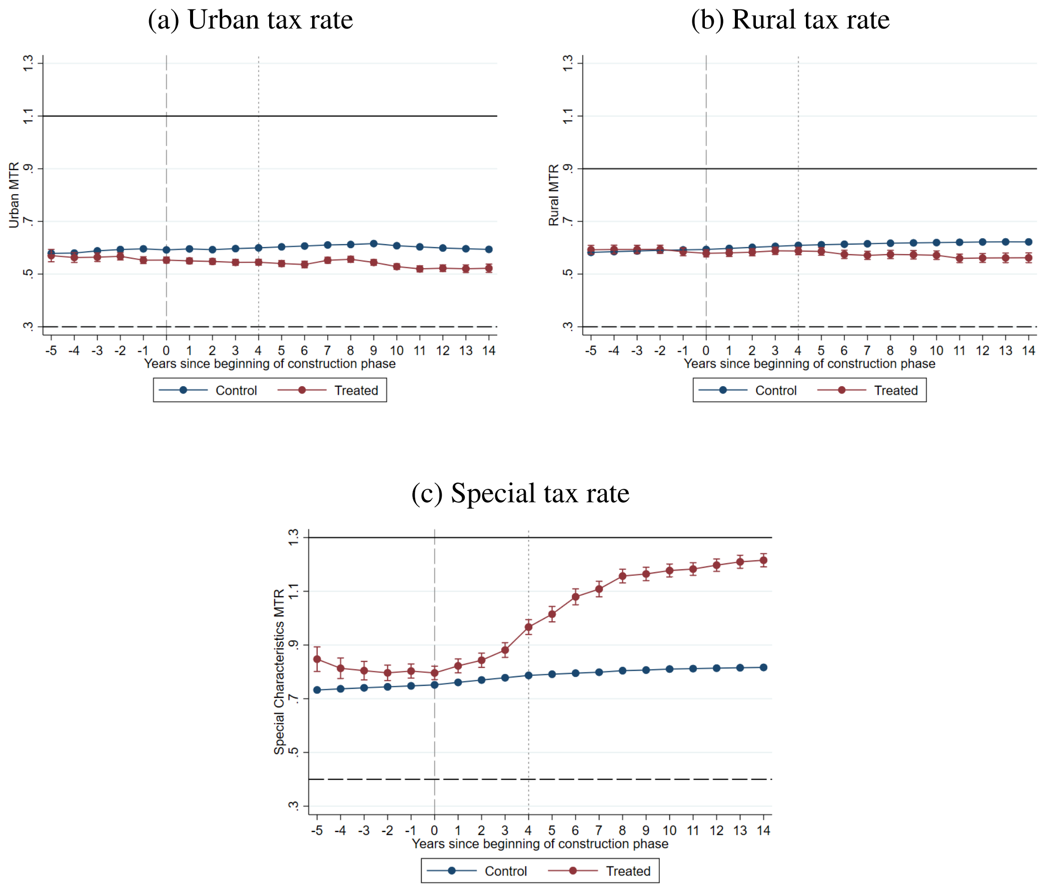
- **Direct taxes**: are mainly composed by property and economic activity taxes.
- **Indirect taxes**: mainly composed by the construction tax.
- **Public prices and fees**: are fees collected for the provision of a service that directly benefits the interested party, such as public land occupation, fees for basic public services provision, or public prices.
- **Current transfers**: composed of transfers from other government levels, both in the participation in state taxes or as subsidies to finance specific activities. Even though transfers from the municipal funding fund are the most important element of this chapter, current transfers can also come from private companies.
- **Capital income**: generated by property rents, bank deposits, or royalty payments and includes concepts such as income from real estate, from concessions and special uses or dividends and profit shares
- **Real investments**: composed by revenue from sales of land and other properties
- **Capital transfers**: which are formed by payments from other administrations or private entities to finance investments and constructions
- **Financial assets**: includes the income derived from the reimbursement of financial assets, such as stocks, shares, bonds, or granted loans
- **Financial liabilities**: includes the income derived from financial operations, mainly loans and credits

Municipal expenditure is composed of the following chapters:

- **Personnel expenses**: which include City Council and civil servants wages
- **Current goods and services**: comprise expenses derived from the operation of the city, including rents, maintenance, and repairs activities as well as utilities and materials
- **Financial expenses**: corresponding to the payment of interest on the loans or credits
- **Current transfers**: grants and subsidies granted to citizens and other entities
- **Real investments**: includes investments in infrastructure, both in maintenance and repairs as well in the new provision, intangible investments or investments in patrimonial and communal assets
- **Capital transfers**: formed by payments to other administrations or private entities to finance their projects
- **Financial assets**: It includes expenses derived from purchasing financial assets, such as stocks, shares, bonds, or granted loans.
- **Financial liabilities**: includes expenses derived from financial operations, mainly loans, and credits

A.3. Local Tax Responses: Descriptive Evidence

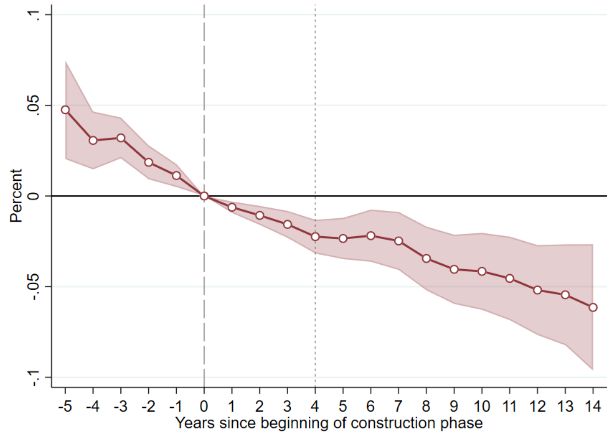
Figure A.3.: Evolution of Property Tax Rates



Notes: Evolution of tax rates in treated and control municipalities. Mean values and standard errors. Reference year (represented by the dashed line) is set at the year before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary register to the energy producers register (dotted line). The solid y-line represents the maximum rate for each of the property tax categories. The dashed y-line represents the minimum rate for each of the property tax categories. Baselines sample restricted to municipalities of less than 20,000 inhabitants not neighboring treated municipalities part of the common tax regime. Municipalities where a wind farm was installed before 2004 are excluded from Panels (a) and (b). Municipalities where a wind farm was installed before 2008 are excluded from Panel (c).

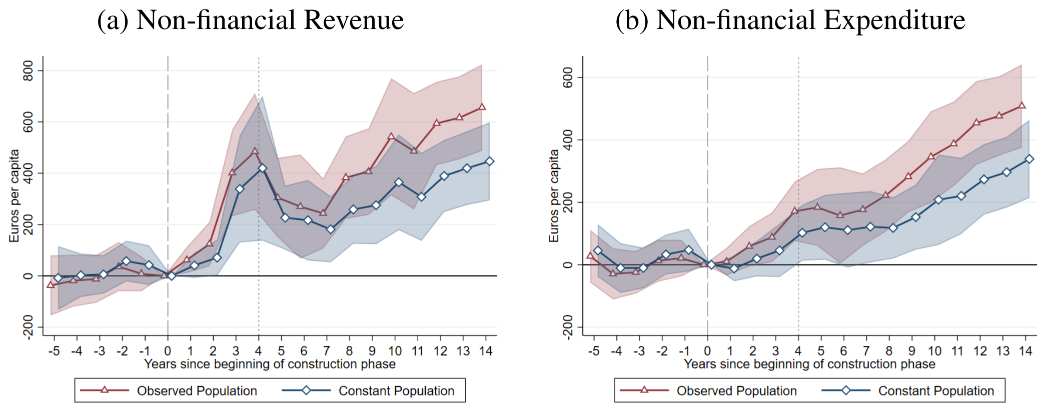
A.4. Population Dynamics

Figure A.4.: Population Dynamics



Notes: Results from estimating the event study model defined by Equation (4.2). The dependent variable is the logarithm of the yearly municipal population. Results correspond to the specification which includes municipality-cohort and year-cohort fixed effects, and uses the sample restricted to municipalities of less than 20,000 inhabitants not neighboring affected units. The reference year (represented by the dashed line) is set at the years before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary register to the energy producers register (dotted line). Standard errors are clustered at the municipality-cohort level. Confidence intervals at the 95 percent level.

Figure A.5.: Effect of Wind Farm Development on Municipal Finances: Exclusion of Population Dynamics



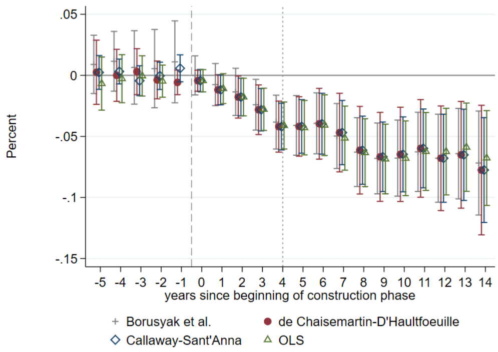
Notes: Results from estimating the event study model defined by Equation (4.2). The dependent variables are non-financial revenue (Panel a) and non-financial expenditure (Panel b). Magnitudes are expressed in per capita terms relative to the yearly municipal population (triangular coefficients in red) and to the 1994 population (rhombus-shaped coefficients in blue). Results correspond to the specification which includes municipality-cohort and year-cohort fixed effects, controls for municipal characteristics and subsequent wind power installations, and uses the sample restricted to municipalities of less than 20,000 inhabitants not neighboring affected units. The reference year (represented by the dashed line) is set at the year before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary register to the energy producers register (dotted line). Standard errors are clustered at the municipality-cohort level. Confidence intervals at the 95 percent level.

B. Robustness Checks

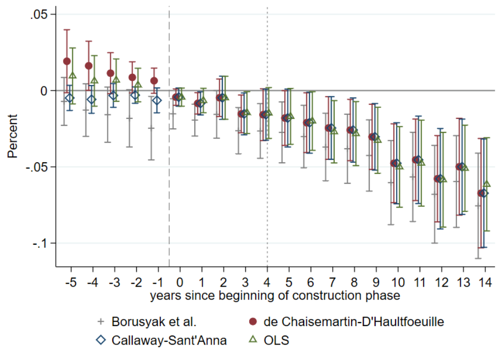
B.1. Alternative DID Estimators

Figure B.1.: Local Tax Responses to Wind Farm Development: Alternative Difference-in-Difference Estimators

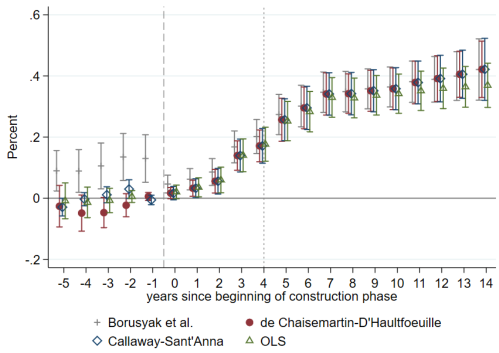
(a) Urban Tax Rate (logs)



(b) Rural Tax Rate (logs)



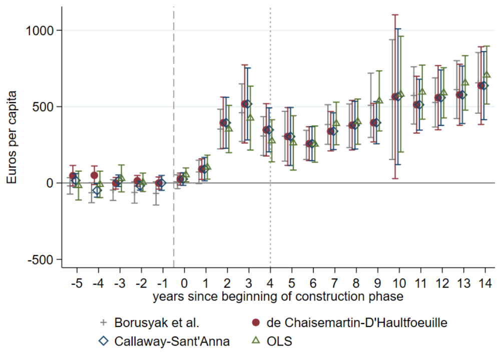
(c) Special Tax Rate (logs)



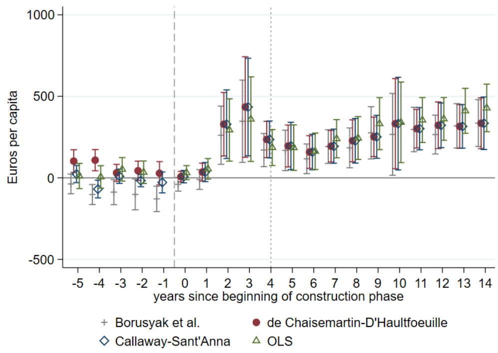
Notes: Results from estimating Equation (4.2) using alternative difference-in-difference estimators. Magnitudes are expressed in logarithms. These results are estimated using the sample restricted to municipalities of less than 20,000 inhabitants not neighboring affected units part of the common tax regime. The reference year (dashed line) is set at three years before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary inscription to the energy producers register (dotted line). Standard errors are clustered at the municipality-cohort level. Confidence intervals at the 95 percent level.

Figure B.2.: Effect of Wind Farm Development on Municipal Finances: Alternative Difference-in-Difference Estimators

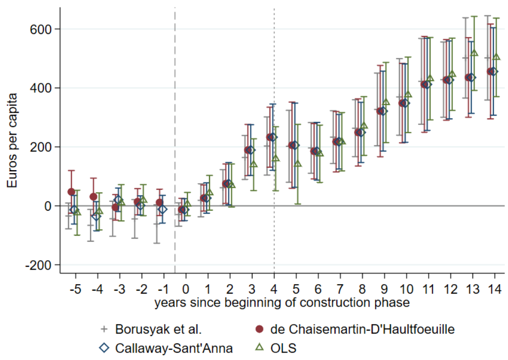
(a) Non-financial Revenue
(euros per capita - observed population)



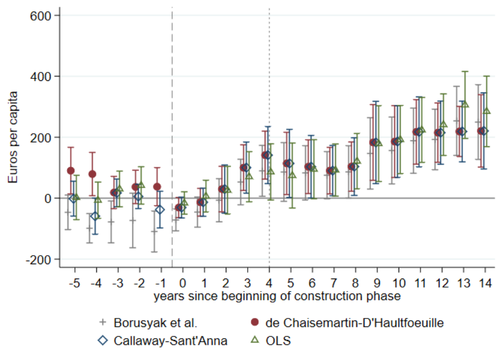
(b) Non-financial Revenue
(euros per capita - 1994 population)



(c) Non-financial Expenditure
(euros per capita - observed population)



(d) Non-financial Expenditure
(euros per capita - 1994 population)



Notes: Results from estimating Equation (4.2) using alternative difference-in-difference estimators. Panels (a) and (c) correspond to magnitudes expressed in per capita terms relative to the observed population. Panels (b) and (d) correspond to magnitudes expressed in per capita terms relative to the 1994 population. These results are estimated using the sample restricted to municipalities of less than 20,000 inhabitants not neighboring affected units. The reference year (dashed line) is set at three years before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary inscription to the energy producers register (dotted line). Standard errors are clustered at the municipality level. Confidence intervals at the 95 percent level.

B.2. Incorporation of Financial Information

Table B.1.: Effect of Wind Farm Development on Municipal Finances: Financial and Non-financial Revenue (euros per capita)

	(1)	(2)	(3)	(4)	(5)
(a) Non-Financial Revenue					
First Installation	248.100***	270.500***	239.300***	276.900***	274.200***
	(57.520)	(57.780)	(58.800)	(64.500)	(64.510)
Mean (treated=1, t=0)	915.462	915.504	915.504	916.826	924.494
R-squared	0.127	0.132	0.132	0.128	0.123
(b) Total Revenue					
First Installation	240.000***	263.500***	231.400***	269.700***	266.900***
	(58.090)	(58.350)	(59.420)	(65.160)	(65.180)
Mean (treated=1, t=0)	955.279	955.327	955.327	954.399	963.287
R-squared	0.125	0.130	0.130	0.127	0.122
N municipalities	8,040	8,040	8,040	7,761	6,865
RFE and TFE	Yes	Yes	Yes	Yes	Yes
Mun Charact	No	Yes	Yes	Yes	Yes
Installed Power	No	No	Yes	Yes	Yes
Excluded Municipalities	No	No	No	>20,000	>20,000
Excluded Neighbors	No	No	No	No	Yes

Notes: Results from estimating the difference-in-difference model described by Equation (4.1). The dependent variables are municipal non-financial revenue (Panel a) and total municipal revenue (Panel b). The magnitudes are expressed in per capita terms relative to the 1994 population. Mean indicates the mean value of the outcome variable for treated municipalities in the period before the development of a wind farm. Controls for municipal characteristics include land use shares and the ideology of the mayor's political party. Installed power controls for subsequent wind power installations accumulated at the municipality-year level. The first treatment year is set at three years before the preliminary registration date. Standard errors are clustered at the municipality-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

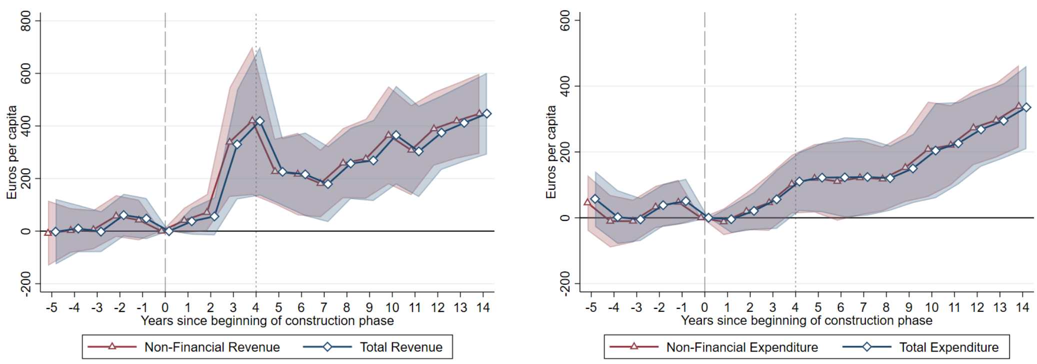
Table B.2.: Effect of Wind Farm Development on Municipal Finances: Financial and Non-financial Expenditure (euros per capita)

	(1)	(2)	(3)	(4)	(5)
		(a) Non-Financial Expenditure			
First Installation	103.800***	124.200***	99.960***	126.000***	123.500***
	(36.520)	(36.700)	(36.990)	(40.280)	(40.290)
Mean (treated=1, t=0)	887.629	887.686	887.686	889.037	896.283
R-squared	0.166	0.172	0.172	0.169	0.164
		(b) Total Expenditure			
First Installation	97.340***	119.200***	95.630**	122.1***	119.100***
	(36.930)	(37.090)	(37.380)	(40.700)	(40.700)
Mean (treated=1, t=0)	915.589	915.650	915.650	915.302	923.316
R-squared	0.168	0.175	0.175	0.171	0.166
N municipalities	8,040	8,040	8,040	7,761	6,865
RFE and TFE	Yes	Yes	Yes	Yes	Yes
Mun Charact	No	Yes	Yes	Yes	Yes
Installed Power	No	No	Yes	Yes	Yes
Excluded Municipalities	No	No	No	>20,000	>20,000
Excluded Neighbors	No	No	No	No	Yes

Notes: Results from estimating the difference-in-difference model described by Equation (4.1) where the dependent variables are municipal non-financial expenditure (Panel a) and total municipal expenditure (Panel b). The magnitudes expressed in per capita terms relative to the 1994 population. Mean indicates the mean value of the outcome variable for treated municipalities in the period of time before the development of a wind farm. Controls for municipal characteristics include land use shares and the ideology of the mayor's political party. Installed power controls for subsequent wind power installations accumulated at the municipality-year level. The first treatment year is set at three years before the preliminary registration date. Standard errors are clustered at the municipality-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.3.: Effect of Wind Farm Development on Municipal Finances: Incorporation of Financial Information

(a) Revenue (b) Expenditure



Notes: Results from estimating the event study model defined by Equation (4.2). Panel (a) shows the results for municipal revenue. Panel (b) shows the results for municipal expenditure. The results from estimating the model with the variables defined without financial information are represented by red triangular coefficients. The point estimates from estimating the model with the variables defined including financial information are represented by blue rhombus-shaped coefficients. The magnitudes are expressed in per capita terms relative to the 1994 population. These results correspond to the specification which includes municipality-cohort and year-cohort fixed effects, controls for municipal characteristics and subsequent wind power installations, and uses the sample restricted to municipalities of less than 20,000 inhabitants not neighboring affected units. The reference year (represented by the dashed line) is set at the year before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary register to the energy producers register (dotted line). Standard errors are clustered at the municipality-cohort level. Confidence intervals at the 95 percent level.

B.3. Restricted Sample

Table B.3.: Effect of Wind Farm Development on Municipal Finances: Non-financial Revenue and Expenditure (euros per capita, 2008-2020)

	(1)	(2)	(3)	(4)	(5)
			(a) Non-financial revenue		
First Installation	584.900***	584.900***	577.700***	632.100***	632.100***
	(139.300)	(140.100)	(144.600)	(156.700)	(156.700)
Mean (treated=1, t=0)	1,377.313	1,377.299	1,377.299	1,378.822	1,395.329
Municipalities	7,235	7,235	7,235	6,949	6,103
R-squared	0.025	0.025	0.025	0.025	0.024
			(b) Non-financial expenditure		
First Installation	227.100***	227.300***	213.400***	242.100***	241.100***
	(53.010)	(53.490)	(53.690)	(57.860)	(57.890)
Mean (treated=1, t=0)	1,323.162	1,323.144	1,323.144	1,324.343	1,339.297
Municipalities	7,235	7,235	7,235	6,949	6,103
R-squared	0.059	0.060	0.060	0.059	0.058
RFE and TFE	Yes	Yes	Yes	Yes	Yes
Mun Charact	No	Yes	Yes	Yes	Yes
Installed Power	No	No	Yes	Yes	Yes
Excluded Municipalities	No	No	No	>20,000	>20,000
Excluded Neighbors	No	No	No	No	Yes

Notes: Results from estimating the difference-in-difference model described by Equation (4.1). The dependent variables are non-financial revenue (Panel a) and non-financial expenditure (Panel b). The magnitudes are expressed in euros per capita relative to the 1994 population. The sample is restricted to municipalities belonging to the common tax regime. Treated municipalities where a wind farm was installed before 2008 are excluded from the sample. Mean indicates the mean marginal tax rate for treated municipalities in the period before the development of a wind farm. Controls for municipal characteristics include land use shares and the ideology of the mayor's political party. Installed power controls for subsequent wind power installations accumulated at the municipality-year level. The first treatment year is set at three years before the preliminary registration date. Standard errors are clustered at the municipality-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

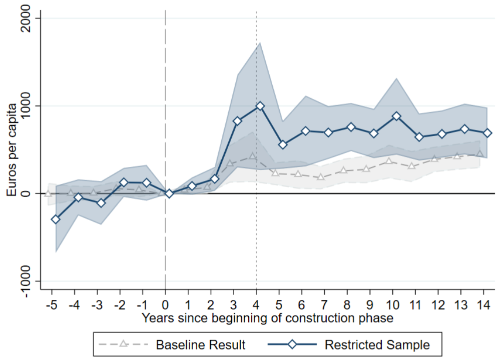
Table B.4.: Local Tax Responses to Wind Farm Development: Property Tax Rates (2008-2020)

	(1)	(2)	(3)	(4)	(5)
		(a) Urban Property Tax			
First Installation	-0.016	-0.019	-0.017	-0.012	-0.011
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Mean (treated=1, t=0)	0.587	0.587	0.587	0.586	0.586
Municipalities	7,281	7,281	7,281	6,995	6,142
R-squared	0.095	0.101	0.101	0.109	0.107
		(b) Rural Property Tax			
First Installation	-0.022**	-0.023**	-0.023**	-0.023**	-0.023**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Mean (treated=1, t=0)	0.602	0.602	0.602	0.601	0.601
Municipalities	7,281	7,281	7,281	6,995	6,142
R-squared	0.048	0.049	0.049	0.051	0.051
RFE and TFE	Yes	Yes	Yes	Yes	Yes
Mun Charact	No	Yes	Yes	Yes	Yes
Installed Power	No	No	Yes	Yes	Yes
Excluded Municipalities	No	No	No	>20,000	>20,000
Excluded Neighbors	No	No	No	No	Yes

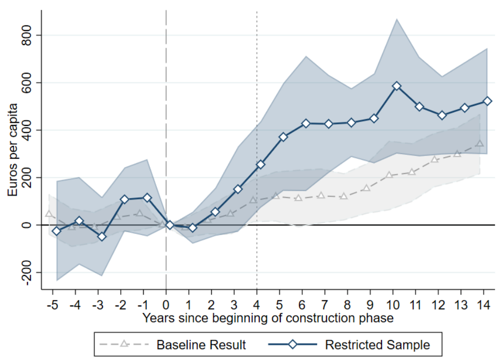
Notes: Results from estimating the difference-in-difference model described by Equation (4.1). The dependent variables are the logarithm of the urban tax rate (Panel a) and the logarithm of the rural tax rate (Panel b). Analysis restricted to municipalities part of the common-tax regime. Treated municipalities where a wind farm was installed before 2008 are excluded from the sample. Mean indicates the mean marginal tax rate for treated municipalities in the period before the development of a wind farm. Controls for municipal characteristics include land use shares and the ideology of the mayor's political party. "Installed power" controls for subsequent wind power installations accumulated at the municipality-year level. The first treatment year is set at three years before the preliminary registration date. Standard errors are clustered at the municipality-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.4.: Dynamic Effect of Wind Farm Development on Municipal Finances (2008-2020)

(a) Non-financial revenue



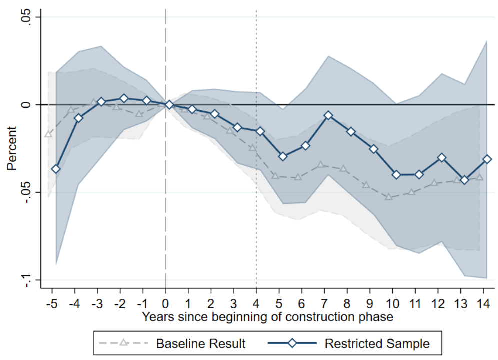
(b) Non-financial expenditure



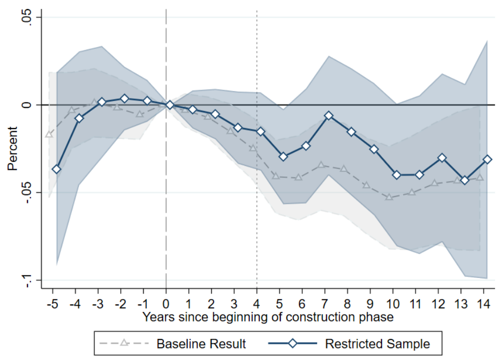
Notes: Results from estimating the event study model defined by Equation (4.2). The dependent variables are non-financial revenue (Panel a) and non-financial expenditure (Panel b). The magnitudes are expressed in euros per capita relative to the 1994 population. Coefficients represented by triangles in gray correspond to the baseline results estimated on the sample of municipalities of less than 20,000 inhabitants not neighboring affected units. Coefficients represented by rhombus in blue correspond to the sample restricted to municipalities belonging to the common tax regime that received the first wind farm starting in 2008. Results correspond to the specification, including municipality-cohort and year-cohort fixed effects, controls for municipal characteristics, and subsequent wind power installations. The reference year (represented by the dashed line) is set at the year before the beginning of the construction phase. The construction phase is considered to start three years before the preliminary register to the energy producers register (dotted line). Standard errors are clustered at the municipality-cohort level. Confidence intervals at the 95 percent level.

Figure B.5.: Dynamic Local Tax Responses to Wind Farm Development: Property Tax Rates (2008-2020)

(a) Urban property tax



(b) Rural property tax



Notes: Results from estimating the event study model defined by Equation (4.2). The dependent variables are the logarithm of the urban (Panel a) and rural (Panel b) tax rates. Coefficients represented by triangles in gray correspond to the baseline results estimated on the sample of municipalities part of the common tax regime that received the first wind farm from 2004 onward. Coefficients represented by rhombus in blue correspond to the sample restricted to municipalities belonging to the common tax regime that received the first wind farm starting in 2008. The sample is restricted to municipalities of less than 20,000 inhabitants not neighboring affected units. Results correspond to the specification which includes municipality-cohort and year-cohort fixed effects, controls for municipal characteristics, and subsequent wind power installations. The reference year (represented by the dashed line) is the year before the construction phase starts. The construction phase is considered to start three years before the preliminary register to the energy producers register (dotted line). Standard errors are clustered at the municipality-cohort level. Confidence intervals at the 95 percent level.

5. Conclusion

Redistributive policies have the potential to mitigate increases in inequality and the polarization of societies by promoting a more equal distribution of resources. Although commonly attributed to spending programs, other public policies such as market regulation or the design of institutions and tax instruments can embed redistributive elements aimed at counteracting self-reinforcing loops of power and wealth accumulation. To minimize the cost-efficiency trade-offs derived from such policies, it is crucial to create space for debate and generate evidence that helps promote more equitable and welfare-enhancing social structures. This dissertation contributes to this debate by exploring redistribution from three different perspectives.

Focusing on the demand side of redistribution, Chapter 2 studies how economic uncertainty induced by labor market institutions affects redistribution demand. In the presence of strong labor market segmentation, risk is unevenly distributed across worker groups and aggregated demand for redistribution may not respond to the needs of workers with lower levels of labor protection. This chapter studies the impact of labor market risk associated with temporary contracts on individual preferences for income redistribution. The Spanish labor market, with one-third of workers employed under temporary contracts, provides a good context for this study. We use data from the European Social Survey from 2008 to 2018 and apply an exact matching methodology to isolate the effect of the contract type from other individual characteristics.

The results discussed in the second chapter reveal that, first, labor market institutions have a significant potential to affect the labor market risk perceived by individuals' and, second, that labor market risk is a strong determinant of redistribution preferences. Beyond individual characteristics and risk exposure within occupation or industries, this analysis shows that the risk induced by the contract type is an important determinant of individual preferences for income redistribution. Our results show that temporary contracts lead to an 11 percent increase in the likelihood of strongly supporting redistribution. Although our results indicate that this effect takes place irrespective of individual's education or gender, we find that the effect is concentrated among individuals aged 40 and above, suggesting an increase in risk perception when this contractual figure becomes a dead end. We complement our analysis of the impact of labor market risk by analyzing heterogeneous effects based on the macroeconomic context. We show that during periods of macroeconomic uncertainty, which extend risk beyond the contract type, preferences for redistribution of temporary and permanent workers equalize due to a substantial increase in the preferences of those with an ex-ante more secure labor market position.

Focusing on redistribution from a tax design perspective, Chapter 3 studies how the decentralization of the Personal Income Tax (PIT) to the sub-national level affects its redistributive effect. This chapter provides evidence of the impact of decentralized personal taxation on income inequality. To do so, we exploit the decentralization of the Spanish Personal Income Tax that took place in 2010 in Spain to document how granting normative power to heterogeneous sub-national regions affected the redistributive effect of the tax. We develop a tax micro-simulation tool that replicates each region and year tax design from 2008 to 2018. We use this tax calculator on individual-level administrative tax records to simulate the redistributive impact of a given tax design when applied to different pre-tax income distributions.

The results discussed in the third chapter are divided into three different blocks. First, we provide descriptive evidence of the stark heterogeneity of the pre-tax income distribution across regions and show that using regions' normative power leads to an average decrease in the regional Gini index of 0.04 points. This reduction in inequality comes from an increase in the income share of the bottom 50 percent at expenses of the income share of those concentrated in the top 10 percent of the distribution. Second, we use our simulation tool to construct counterfactual scenarios in which the tax design of a given region is applied to alternative pre-tax income distributions. By doing so, we show that the reduction of inequality achieved by the tax design is strongly conditioned by the pre-tax income distribution to which it is applied. Last, we document efficiency effects of the tax by applying the methodology of Zidar (2019). This methodology exploits the heterogeneous impacts of national tax shocks due to regional differences in income distributions. Our results indicate that tax hikes on the rich are reflected by wage increases, while we find little effects on employment and output. This exercise shows that the decentralization of the PIT increased its redistributive effect, and did not generate any efficiency cost for those on the bottom of the income distribution.

Chapter 4 focuses on the costs and benefits derived from the green energy transition by studying the effect of wind farm development on municipal finances and local tax responses. The development of wind energy infrastructure encompasses global benefits and can offer opportunities for rural areas. Yet, its development can also generate local negative externalities that are geographically concentrated. This chapter studies whether the development of wind farms causes revenue windfalls as the base of existing tax instruments increases and hence benefits financially receiving municipalities. To do so, I focus on the development of wind farms in Spain, the second-largest European country in terms of installed wind capacity. I combine Spanish municipality-level budget data from 1994 to 2020 with information on the development of wind farms from the Spanish Register of Energy Producers. To provide a clear causal identification of their local effects, I use difference-in-differences and event-study methodologies that exploit spatial and temporal variations in the development of wind energy installations.

The results presented in the fourth chapter indicate that the development of a wind farm results in an average 30 percent increase in municipal revenue per capita. These additional funds are primarily allocated toward financing real investments and current expenditures. I complement the analysis of the revenue effect by decomposing it into its main categories and show that the effect is driven by different mechanisms along the lifetime of the wind farm. Although during the construction phase the effect is driven by an increase in revenue from indirect taxes, once it becomes operative the revenue effect comes from an increase in revenue from direct taxes. The results show that these revenue windfalls, partially driven by an increase in the tax base, are complemented by local tax responses. Municipalities react to the development of a wind farm by increasing tax rates associated with this type of non-mobile capital investment close to their maximum levels, while decreasing the fiscal pressure associated with other property tax categories.

The results presented in the previous chapters point toward important policy implications and avenues for future research. The results of Chapter 2 indicate that institutions, and particularly those related to the labor market, have an important role in determining the economic structure and inequality level of societies. If aggregated redistribution demand is determined by the risk perception of those in more protected positions, significant gaps in employment protection and extensive use of temporary contracts imply that political support for those categories of social insurance that would benefit those in less protected positions is reduced as their insurance demand is underrepresented. Thus, designing labor market institutions to mitigate labor market polarization and implementing policies reducing the employment protection gap between temporary and permanent workers could help ensure an adequate level of social insurance independently of individuals' labor contracts.

The analysis presented in Chapter 3 shows that decentralizing the tax design allows regions to adapt their design to their pre-tax income distributions. The exercises we perform with our micro-simulation tool demonstrate that the effect of the PIT on the reduction of inequality is strongly conditioned by the pre-tax income distribution. The conclusions that derive from this chapter provide evidence that the decentralization of the PIT can increase its effect in terms of the reduction of inequality as it allows to implement different tax design over regions. Yet, our analysis estimates average effects and does not reflect that regions used their normative power to deviate from the central-level design in different directions. Thus, an important avenue left to study are the determinants of regional tax policy. Understanding the interaction of factors determining regional tax designs such as political preferences, adaptations to pre-tax distributions, or financial needs, is an important step to better understand the implications of tax decentralization. The results illustrating the relevance of the pre-tax income distribution in determining the redistributive capacity of the tax design point to the importance of pre-distributive policies in counteracting inequality increases and the relevance of analyzing the equity effects of tax shocks. To better identify the incidence effects of tax policy, the analysis should move beyond aggregate measures and study employment and wage effects along the income distribution.

Last, Chapter 4 shows that municipalities financially benefit from the development of wind farms in their territory. Yet, local opposition to new developments is still present. There are several factors that can cause this opposition. The limitation of municipalities' expenditure competencies, the extension of negative externalities associated with wind farms beyond municipality areas, the concentration of land tenure, or the heterogeneous use of resources depending on the political ideology of the municipality could be factors helping to understand this opposition. Gaining knowledge on the interplay of these forces is a necessary step to promote a more efficient and socially inclusive green energy transition.

References

Alesina, A., and Glaeser, E. (2004). *Fighting poverty in the us and europe: A world of difference*. Oxford University Press.

Alesina, A., Stantcheva, S., and Teso, E. (2018). Intergenerational mobility and preferences for redistribution. *American Economic Review*, *108*(2), 521–554.

Allan, G., Comerford, D., Connolly, K., McGregor, P., and Ross, A. G. (2020). The economic and environmental impacts of uk offshore wind development: The importance of local content. *Energy*, *199*, 117436.

Alt, J., and Iversen, T. (2017). Inequality, labor market segmentation, and preferences for redistribution. *American Journal of Political Science*, *61*(1), 21–36.

Amuedo-Dorantes, C. (2000). Work transitions into and out of involuntary temporary employment in a segmented market: Evidence from spain. *ILR Review*, *53*(2), 309–325.

Anderson, C. J., and Pontusson, J. (2007). Workers, worries and welfare states: Social protection and job insecurity in 15 oecd countries. *European Journal of Political Research*, *46*(2), 211–235.

Bargain, O., and Callan, T. (2010). Analysing the effects of tax-benefit reforms on income distribution: A decomposition approach. *The Journal of Economic Inequality*, *8*(1), 1–21.

Bartik, A. W., Currie, J., Greenstone, M., and Knittel, C. R. (2019). The local economic and welfare consequences of hydraulic fracturing. *American Economic Journal: Applied Economics*, *11*(4), 105–55.

Bartoll, X., Gil, J., and Ramos, R. (2018). Has the economic crisis worsened the work-related stress and mental health of temporary workers in spain?

Bentolila, S., Dolado, J. J., and Jimeno, J. F. (2012). Reforming an insider-outsider labor market: The spanish experience. *IZA Journal of European Labor Studies*, *1*(1), 4.

Bentolila, S., Dolado, J. J., and Jimeno, J. F. (2020). Dual labor markets revisited.

Bentolila, S., Dolado, J. J., and Jimeno, J. F. (2008). Two-tier employment protection reforms: The spanish experience. *CESifo DICE Report*, *6*(4), 49–56.

Berton, F., and Garibaldi, P. (2012). Workers and firms sorting into temporary jobs. *The Economic Journal*, *122*(562), F125–F154.

Blackwell, M., Iacus, S. M., King, G., and Porro, G. (2009). Cem: Coarsened exact matching in stata. *The Stata Journal*, *9*(4), 524–546.

Booth, A. L., Francesconi, M., and Frank, J. (2002). Temporary jobs: Stepping stones or dead ends? *The economic journal*, *112*(480), F189–F213.

Borusyak, K., Jaravel, X., and Spiess, J. (2021). Revisiting event study designs: Robust and efficient estimation. *arXiv preprint arXiv:2108.12419*.

Bozio, A., Garbinti, B., Goupille-Lebret, J., Guillot, M., Piketty, T., et al. (2018). Inequality and redistribution in france, 1990-2018: Evidence from post-tax distributional national accounts (dina). *World Inequality Lab Working Papers*, (2018/10).

Brown, J. P., et al. (2014). Production of natural gas from shale in local economies: A resource blessing or curse. *Economic Review*, *99*(1), 119–147.

Brown, J. P., Pender, J., Wiser, R., Lantz, E., and Hoen, B. (2012). Ex post analysis of economic impacts from wind power development in us counties. *Energy Economics*, *34*(6), 1743–1754.

Brunner, E., Hoen, B., and Hyman, J. (2022). School district revenue shocks, resource allocations, and student achievement: Evidence from the universe of us wind energy installations. *Journal of Public Economics*, *206*, 104586.

Brunner, E. J., and Schwegman, D. J. (2022). Windfall revenues from windfarms: How do county governments respond to increases in the local tax base induced by wind energy installations? *Public Budgeting and Finance*, *42*(3), 93–113.

Burgoon, B., and Dekker, F. (2010). Flexible employment, economic insecurity and social policy preferences in europe. *Journal of European Social Policy*, *20*(2), 126–141.

Callaway, B., and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230.

Cantante, F. (2020). Four profiles of inequality and tax redistribution in europe. *Humanities and Social Sciences Communications*, *7*(1), 1–7.

Castañer, J. M., Onrubia*, J., and Paredes, R. (2004). Evaluating social welfare and redistributive effects of spanish personal income tax reform. *Applied Economics*, *36*(14), 1561–1568.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, *134*(3), 1405–1454.

Clausen, L. T., and Rudolph, D. (2020). Renewable energy for sustainable rural development: Synergies and mismatches. *Energy Policy*, *138*, 111289.

Copena, D., and Simón, X. (2018). Wind farms and payments to landowners: Opportunities for rural development for the case of galicia. *Renewable and Sustainable Energy Reviews*, *95*, 38–47.

Corneo, G., and Grüner, H. P. (2002). Individual preferences for political redistribution. *Journal of public Economics*, *83*(1), 83–107.

Costa, H., and Veiga, L. (2021). Local labor impact of wind energy investment: An analysis of portuguese municipalities. *Energy Economics*, *94*, 105055.

Cullen, J. (2013). Measuring the environmental benefits of wind-generated electricity. *American Economic Journal: Economic Policy*, *5*(4), 107–133.

Cusack, T., Iversen, T., and Rehm, P. (2006). Risks at work: The demand and supply sides of government redistribution. *Oxford Review of Economic Policy*, *22*(3), 365–389.

Dardanoni, V., and Lambert, P. J. (2002). Progressivity comparisons. *Journal of Public Economics*, *86*(1), 99–122.

De Chaisemartin, C., and D'Haultfoeuille, X. (2022a). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. *National Bureau of Economic Research*, (29734). https://doi.org/10.3386/w29734

De Chaisemartin, C., and D'Haultfoeuille, X. (2022b). Difference-in-differences estimators of intertemporal treatment effects. *National Bureau of Economic Research*, (29873). https://doi.org/10.3386/w29873

De Silva, D. G., McComb, R. P., and Schiller, A. R. (2016). What blows in with the wind? *Southern Economic Journal*, *82*(3), 826–858.

Díaz Caro, C., Onrubia Fernández, J., and Pérez Mayo, J. (2013). Progresividad y redistribución por fuentes de renta en el irpf dual. *Hacienda Pública Española/Review of Public Economics*, (206), 57–87.

Dimick, M., Rueda, D., and Stegmueller, D. (2018). Models of other-regarding preferences, inequality, and redistribution. *Annual Review of Political Science*, *21*, 441–460.

Dolado, J. J. (2017). European union dual labour markets: Consequences and potential reforms. *Economics without Borders: Economic Research for European Policy Challenges, Cambridge University Press, Cambridge*, 73–112.

Dolado, J. J., Garcıa-Serrano, C., and Jimeno, J. F. (2002). Drawing lessons from the boom of temporary jobs in spain. *The Economic Journal*, *112*(480), F270–F295.

Dröes, M. I., and Koster, H. R. (2021). Wind turbines, solar farms, and house prices. *Energy Policy*, *155*, 112327.

Ejdemo, T., and Söderholm, P. (2015). Wind power, regional development and benefit-sharing: The case of northern sweden. *Renewable and Sustainable Energy Reviews*, *47*, 476–485.

Fabra, N., Gutierrez, E., Lacuesta, A., and Ramos, R. (2023). Do renewables create local jobs? *Banco de España*, (2307).

Feenberg, D., and Coutts, E. (1993). An introduction to the taxsim model. *Journal of Policy Analysis and management*, *12*(1), 189–194.

Fernández-Albertos, J., and Manzano, D. (2016). Dualism and support for the welfare state. *Comparative European Politics*, *14*(3), 349–375.

Finseraas, H. (2009). Income inequality and demand for redistribution: A multilevel analysis of european public opinion. *Scandinavian Political Studies*, *32*(1), 94–119.

Finseraas, H. (2012). Poverty, ethnic minorities among the poor, and preferences for redistribution in european regions. *Journal of European Social Policy*, *22*(2), 164–180.

Gagliarducci, S. (2005). The dynamics of repeated temporary jobs. *Labour Economics*, *12*(4), 429–448.

García-Pérez, J. I., Marinescu, I., and Vall Castello, J. (2018). Can fixed-term contracts put low skilled youth on a better career path? evidence from spain. *The Economic Journal*, *129*(620), 1693–1730.

García-Pérez, J. I., and Muñoz-Bullón, F. (2011). Transitions into permanent employment in spain: An empirical analysis for young workers. *British Journal of Industrial Relations*, *49*(1), 103–143.

Garcıa-Miralles, E., Guner, N., and Ramos, R. (2019). The spanish personal income tax: Facts and parametric estimates. *SERIEs*, *10*(3), 439–477.

Gibbons, S. (2015). Gone with the wind: Valuing the visual impacts of wind turbines through house prices. *Journal of Environmental Economics and Management*, *72*, 177–196.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277.

Green, F. (2020). Health effects of job insecurity. *IZA World of labor*.

Guadalupe, M. (2003). The hidden costs of fixed term contracts: The impact on work accidents. *Labour economics*, *10*(3), 339–357.

Güell, M., and Petrongolo, B. (2007). How binding are legal limits? transitions from temporary to permanent work in spain. *Labour Economics*, *14*(2), 153–183.

Guner, N., López-Segovia, J., and Ramos, R. (2020). Reforming the individual income tax in spain. *SERIEs*, *11*(4), 369–406.

Hartley, P. R., Medlock III, K. B., Temzelides, T., and Zhang, X. (2015). Local employment impact from competing energy sources: Shale gas versus wind generation in texas. *Energy economics*, *49*, 610–619.

Häusermann, S., Kurer, T., and Schwander, H. (2015). High-skilled outsiders? labor market vulnerability, education and welfare state preferences. *Socio-Economic Review*, *13*(2), 235–258.

Häusermann, S., Kurer, T., and Schwander, H. (2016). Sharing the risk? households, labor market vulnerability, and social policy preferences in western europe. *The journal of politics*, *78*(4), 1045–1060.

Iacus, S. M., King, G., and Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political analysis*, *20*(1), 1–24.

Iversen, T., and Soskice, D. (2001). An asset theory of social policy preferences. *American Political Science Review*, *95*(4), 875–893.

Izquierdo, M., Puente, S., Regil, A., et al. (2021). Los erte en la crisis del covid-19: Un primer análisis de la reincorporación al empleo de los trabajadores afectados. *Boletín económico*, (2/2021), 1–13.

Jarvis, S., et al. (2021). The economic costs of nimbyism-evidence from renewable energy projects. *WP*.

Jensen, C. U., Panduro, T. E., Lundhede, T. H., Nielsen, A. S. E., Dalsgaard, M., and Thorsen, B. J. (2018). The impact of on-shore and off-shore wind turbine farms on property prices. *Energy policy*, *116*, 50–59.

Komarek, T. M. (2016). Labor market dynamics and the unconventional natural gas boom: Evidence from the marcellus region. *Resource and Energy Economics*, *45*, 1–17.

Kristjánsson, A. S. (2011). Income redistribution in iceland: Development and european comparisons. *European Journal of Social Security*, *13*(4), 392–423.

Lambert, P. J. (1992). The distribution and redistribution of income. In *Current issues in public sector economics* (pp. 200–226). Springer.

Lambert, P. J., and Thoresen, T. O. (2009). Base independence in the analysis of tax policy effects: With an application to norway 1992–2004. *International Tax and Public Finance*, *16*(2), 219–252.

Langenmayr, D., and Simmler, M. (2021). Firm mobility and jurisdictions' tax rate choices: Evidence from immobile firm entry. *Journal of Public Economics*, *204*, 104530.

Lehr, U., Lutz, C., and Edler, D. (2012). Green jobs? economic impacts of renewable energy in germany. *Energy Policy*, *47*, 358–364.

Lupu, N., and Pontusson, J. (2011). The structure of inequality and the politics of redistribution. *American Political Science Review*, *105*(2), 316–336.

Marchand, J., and Weber, J. G. (2020). How local economic conditions affect school finances, teacher quality, and student achievement: Evidence from the texas shale boom. *Journal of Policy Analysis and Management*, *39*(1), 36–63.

Margalit, Y. (2013). Explaining social policy preferences: Evidence from the great recession. *American Political Science Review*, *107*(1), 80–103.

Margalit, Y. (2019). Political responses to economic shocks. *Annual Review of Political Science*, *22*, 277–295.

Marx, P. (2014). Labour market risks and political preferences: The case of temporary employment. *European Journal of Political Research*, *53*(1), 136–159.

Marx, P., and Picot, G. (2013). The party preferences of atypical workers in germany. *Journal of European social policy*, *23*(2), 164–178.

Marx, P., and Picot, G. (2020). Three approaches to labor-market vulnerability and political preferences. *Political Science Research and Methods*, *8*(2), 356–361.

Mauritzen, J. (2020). Will the locals benefit?: The effect of wind power investments on rural wages. *Energy policy*, *142*, 111489.

Meltzer, A. H., and Richard, S. F. (1981). A rational theory of the size of government. *Journal of political Economy*, *89*(5), 914–927.

Michaud, P.-C., Crimmins, E. M., and Hurd, M. D. (2016). The effect of job loss on health: Evidence from biomarkers. *Labour economics*, *41*, 194–203.

Milligan, K., and Smart, M. (2019). An estimable model of income redistribution in a federation: Musgrave meets oates. *American Economic Journal: Economic Policy*, *11*(1), 406–34.

Mirrlees, J. A. (1971). An exploration in the theory of optimum income taxation. *The review of economic studies*, *38*(2), 175–208.

Moene, K. O., and Wallerstein, M. (2001). Inequality, social insurance, and redistribution. *American Political Science Review*, *95*(4), 859–874.

Musgrave, R. A. (1959). *The theory of public finance; a study in public economy*. Kogakusha Co.

Newell, R. G., and Raimi, D. (2015). Oil and gas revenue allocation to local governments in eight states. *National Bureau of Economic Research*.

Novan, K. (2015). Valuing the wind: Renewable energy policies and air pollution avoided. *American Economic Journal: Economic Policy*, *7*(3), 291–326.

Oates, W. E. (1972). Fiscal federalism. *Books*.

OECD. (2002). Taking the measure of temporary employment. *Employment Outlook*, 135–196.

Onrubia, J., Picos-Sánchez, F., and del Carmen Rodado, M. (2014). Rethinking the pfähler–lambert decomposition to analyse real-world personal income taxes. *International Tax and Public Finance*, *21*(4), 796–812.

Ortega, E., and Peñalosa, J. (2013). Algunas reflexiones sobre la economía española tras cinco años de crisis. *Banco de España. Documentos Ocasionales*, (1304).

Pfähler, W. (1990). Redistributive effect of income taxation: Decomposing tax base and tax rates effects. *Bulletin of Economic Research*, *42*(2), 121–129.

Polavieja, J. G. (2006). The incidence of temporary employment in advanced economies: Why is spain different? *European Sociological Review*, *22*(1), 61–78.

Rahman, A., Farrok, O., and Haque, M. M. (2022). Environmental impact of renewable energy source based electrical power plants: Solar, wind, hydroelectric, biomass, geothermal, tidal, ocean, and osmotic. *Renewable and Sustainable Energy Reviews*, *161*, 112279.

Ravallion, M., and Lokshin, M. (2000). Who wants to redistribute?: The tunnel effect in 1990s russia. *Journal of public Economics*, *76*(1), 87–104.

Rehm, P. (2009). Risks and redistribution: An individual-level analysis. *Comparative political studies*, *42*(7), 855–881.

Rehm, P. (2011). Social policy by popular demand. *World Politics*, *63*(2), 271–299.

Rehm, P., Hacker, J. S., and Schlesinger, M. (2012). Insecure alliances: Risk, inequality, and support for the welfare state. *American political science review*, *106*(2), 386–406.

Rovny, A. E., and Rovny, J. (2017). Outsiders at the ballot box: Operationalizations and political consequences of the insider–outsider dualism. *Socio-Economic Review*, *15*(1), 161–185.

Rueda, D. (2005). Insider–outsider politics in industrialized democracies: The challenge to social democratic parties. *American political science review*, *99*(1), 61–74.

Rueda, D. (2007). *Social democracy inside out: Partisanship and labor market policy in advanced industrialized democracies*. Oxford University Press on Demand.

Schiermeier, Q., Tollefson, J., Scully, T., Witze, A., and Morton, O. (2008). Electricity without carbon. *Nature*, *454*(7206), 816–824.

Schwander, H. (2019). Labor market dualization and insider–outsider divides: Why this new conflict matters. *Political Studies Review*, *17*(1), 14–29.

Serrano-Puente, D. (2020). Optimal progressivity of personal income tax: A general equilibrium evaluation for spain. *SERIEs*, *11*(4), 407–455.

Shoeib, E. A. H., Renski, H. C., and Infield, E. H. (2022). Who benefits from renewable electricity? the differential effect of wind power development on rural counties in the united states. *Energy Research and Social Science*, *85*, 102398.

Shorrocks, A. F. (2013). Decomposition procedures for distributional analysis: A unified framework based on the shapley value. *Journal of Economic Inequality*, *11*(1), 99.

Slattery, M. C., Lantz, E., and Johnson, B. L. (2011). State and local economic impacts from wind energy projects: Texas case study. *Energy Policy*, *39*(12), 7930–7940.

Sunak, Y., and Madlener, R. (2016). The impact of wind farm visibility on property values: A spatial difference-in-differences analysis. *Energy Economics*, *55*, 79–91.

Sutherland, H., and Figari, F. (2013). Euromod: The european union tax-benefit microsimulation model. *International journal of microsimulation*, *6*(1), 4–26.

Thoresen, T. O., Bø, E. E., Fjærli, E., and Halvorsen, E. (2012). A suggestion for evaluating the redistributional effects of tax changes: With an application to the 2006 norwegian tax reform. *Public Finance Review*, *40*(3), 303–338.

Thoresen, T. O., Jia, Z., and Lambert, P. J. (2016). Is there more redistribution now? a review of methods for evaluating tax redistributional effects. *Finanz-Archiv: Zeitschrift für das Gesamte Finanzwesen*, *72*(3), 302.

Wagstaff, A., and Van Doorslaer, E. (2001). What makes the personal income tax progressive? a comparative analysis for fifteen oecd countries. *International Tax and Public Finance*, *8*(3), 299–316.

Wang, C., Caminada, K., and Goudswaard, K. (2014). Income redistribution in 20 countries over time. *International Journal of Social Welfare*, *23*(3), 262–275.

Weber, J. G., Burnett, J. W., and Xiarchos, I. M. (2016). Broadening benefits from natural resource extraction: Housing values and taxation of natural gas wells as property. *Journal of Policy Analysis and Management*, *35*(3), 587–614.

Wolsink, M. (2007). Planning of renewables schemes: Deliberative and fair decision-making on landscape issues instead of reproachful accusations of non-cooperation. *Energy policy*, *35*(5), 2692–2704.

Zidar, O. (2019). Tax cuts for whom? heterogeneous effects of income tax changes on growth and employment. *Journal of Political Economy*, *127*(3), 1437–1472.

Ziegler, L., Gonzalez, E., Rubert, T., Smolka, U., and Melero, J. J. (2018). Lifetime extension of onshore wind turbines: A review covering germany, spain, denmark, and the uk. *Renewable and Sustainable Energy Reviews*, *82*, 1261–1271.