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PhD Thesis

Essays on Political Trust and Economic Opportunities

Department of Economics and Law

PhD in Socio-Economic and Statistical Studies (XXXVII cycle)

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Introduction

Political trust, social cohesion, and equal opportunities are essential elements for stable and fair democracies. In the last few decades, however, Europe has gone through major economic and social changes that have challenged these principles. Repeated economic crises have increased inequality, while the fast development of digital technologies has changed the way citizens receive and share political information. As these two forces interact, leading to more polarization and growing distrust toward democratic institutions, understanding how different means of information and socioeconomic conditions may affect public confidence is therefore crucial for building more resilient and inclusive societies.

This thesis attempts to study these issues by examining the links between information, inequality, and opportunity as key factors behind political trust. The three chapters approach this question from different perspectives, proposing both methodological tools and empirical analyses to explore individual and societal dimensions of trust.

The first chapter examines how the use of the Internet has influenced political trust in Italy between 2014 and 2022. Using individual-level data, it explores the relationship between online political information and citizens' confidence in political institutions, finding a robust negative association. However, this link is not uniform: while exposure to social media, where misinformation is often widespread, tends to lower political trust, the use of online newspapers appears to be associated with higher confidence in institutions. These patterns illustrate the dual role of digital media in shaping political attitudes and raise important questions about the long-term effects of online information on democratic stability.

Driven by these long-term concerns, the second chapter turns to the structural dimension of trust, examining how socioeconomic inequality affect confidence in supranational institutions across Europe. To analyze these patterns, it introduces a non-parametric tool, the Trust Dynamics Curve (TDC), which measures changes in political trust across different social groups in an attempt to overcome some of the limitations of approaches based on categorical variables. In parallel, the chapter proposes a normative framework to understand the welfare implications of trust dynamics and to assess how major economic shocks have influenced different segments of the population. Within this framework, it also compares two alternative criteria for examining welfare dynamics across socioeconomic groups: one based on income inequality and the other on inequality of opportunity. Using data from the European Social Survey (ESS), the analysis underlines that economic disparities and background circumstances play a key role in explaining variations in trust and reveal distinct patterns across different groups.

As the discussion in Chapter 2 leaves open debate about the relationship between income inequality and fairness considerations, and how these two dimensions may shape political trust in different ways, the third chapter shifts the focus to the literature on equality of opportunity, proposing an individual measure grounded in this framework.

Specifically, Chapter 3 proposes a measure of individual Sensitivity to Effort, designed to capture how much people can influence their economic outcomes given their initial circumstances. Building on Roemer's Identification Assumption (RIA), the measure represents the local steepness of the inverse cumulative distribution function (CDF) for type-specific income distributions, which is estimated using adaptive kernel density methods. When applied to the first wave of the UK Understanding Society dataset, the results show substantial variation within types, offering a new perspective on fairness within society.

Taken together, the three studies offer a comprehensive view of how digital information, social inequality, and individual effort shape trust and opportunity in today's democracies. By combining empirical analysis with theoretical discussion, the thesis attempts to better understand the factors that strengthen or weaken people's confidence in institutions and offers ideas to help restore it.

Chapter 1

Information Consumption and Political Trust in Italy: Is the Internet Bad? It Depends.[1]

Matteo Sabatini[2]

Abstract

Political distrust is a pervasive and worrying phenomenon in modern societies, as it represents a threat to the sustainability of democratic systems. Shedding light on its determinants is therefore fundamental to ensuring a lasting and stable social contract. This paper devotes specific attention to the effect of Internet use to acquire political information on political trust, proxied by a composite indicator of confidence in several political institutions. Using individual data from a sample of the Italian population over the period 2014–2022, the results reveal a robust negative relationship between exposure to political information obtained through the web and confidence in governing institutions, but this relationship hides some countervailing effects even after controlling for endogeneity issues. When distinguishing among different modes of online information acquisition, political trust is negatively related to the consumption of political information only when this information is obtained through social networks, where the risk of exposure to fake news is higher. It is, instead, positively related to online political information when this information is accessed through online newspapers.

[1]This work is based on a joint paper with Professor Flaviana Palmisano, Department of Economics and Law, Sapienza University of Rome.

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1.1 Introduction

Restoring trust in government and public authorities – what may be called political trust – has been a major concern in the political agenda of European and national institutions, especially after the 2008 financial crisis and the Covid-19 pandemic.[3]

Political trust is crucial for the governance of modern states: it leads to greater compliance with public policies, fosters civic engagement and political participation, and gives legitimacy and sustainability to a country's democratic system(Besley, 2020; OECD., 2022). Hence, political trust represents one of the main pillars of social cohesion; it sets the basis for people to trust each other, warning that uncivil behaviors will be sanctioned, thus becoming a deterrent against such actions(Rothstein & Stolle, 2008). Arguably, governments perceived as trustworthy, able to enforce the law and keep tax legislation stable, will generate an upward spiral leading to more investment in both physical and human capital, which will be finally reflected into higher economic growth (Bjørnskov, 2009; Knack & Keefer, 1997).

Especially, during periods of crisis and uncertainty toward the future, high political distrust can result in the governments' inability to carry out the necessary recovery plans and policies. The recurrence of black-swan events (the Covid pandemic, the Russian-Ukrainian and Israeli-Palestinian conflicts) that is characterizing the contemporary society makes then clear why it is problematic that we currently seem to be in the midst of a crisis of trust. Thus, understanding the roots of political distrust becomes compelling.

The literature identifies a variety of explanations and contributory factors for declining political trust, including the impact of economic, institutional, and cultural characteristics (see Algan *et al.* (2017); Kaasa & Andriani (2022); Guiso *et al.* (2019); Ivanov (2023); Ligthart & van Oudheusden (2015)among others). Within this literature specific attention has been devoted to the role played by different forms of spreading information (Porumbescu, 2015; Knoll *et al.*, 2023). Trust in turn depends on knowledge about the likely trustworthiness of the person or thing to be trusted. Problems associated with the information (disorder) upon which we base our assessment about the trustworthiness of other actors can therefore have profoundly negative repercussion for political trust. Indeed, in the difficult path to restore confidence, governments are facing a further threat, hidden behind the newest forms of communication, revolutionized by the massive use of social networks and able to lead to (mis)perceptions and affect political results (Klein & Robison, 2020).

The spread of social media in our society has drastically transformed citizens' habits and customs. It has affected not only the way in which individuals interact with each other, but also the way they obtain, produce, and exchange information (Campante *et al.*, 2018), with massive implication on the diffusion of its content. With the growing expansion of internet use and social media, information is spread unfiltered very rapidly. This represents a potential challenge to the quality of the information and facilitates the diffusion of bias and polarizing contents (Allcott *et al.*, 2020) that tend to increase the perception of political corruption and ineffectiveness, which in turn makes government more vulnerable (Edmond, 2013). The concerns of this situation have been expressed by many international institutions. The OECD, for instance, has recently

[3]See for examples (OECD., 2022) and European Central Bank (2022).

stressed how "access to accurate information is a key component of democracy and a foundation of trust" (OECD., 2022). In the same vein, the World Health Organization has added, referring to the pandemic, that the spread of news online "can surely help to fill information voids more quickly but can also amplify harmful messages, potentially leading to mistrust in authorities and undermines the public health response"(World Health Organization 2020).

Thus, increasing awareness about the role played by this information revolution in shaping citizens' attitudes toward their reference institutions is of primary importance. It is to this field of the literature that we intend to contribute. Specifically, we aim at deepening the general understanding of the relationship between the modality of information consumption and political trust.

Using data extracted from the "Multi-purpose Survey on Families: Aspects of Daily Life" a survey conducted annually by the Italian National Institute of Statistics, for the period 2014-2022, our results suggest that the use of internet to remain informed about political facts is negatively associated with political trust, but this negative association can hide some troubling countervailing effects. When the whole set of modalities to get information through internet is considered, trust is negatively related to online information acquired through social media but positively associated with online information acquired through online newspapers. Thus, limiting the analysis to simply considering internet diffusion – as done by the existing literature – would only capture an average effect and hide a more complex underlying nexus between internet diffusion and political trust. When zooming on the years of the pandemics, our analysis also witnesses that one possible explanation for this countervailing effect is represented by exposure to fake news, whose risk is higher in the social network virtual reality. Our results survive a set of robustness checks including those performed to control for potential endogeneity issues.

Differently from recent empirical evidence on the determinants of institutional trust (Kaasa & Andriani, 2022; Bellantuono *et al.*, 2023; Bobzien, 2023) using big data techniques and multilevel analysis, this paper adopts estimation methods that allow for a comprehensive examination of potential endogeneity problems and rely on a method that can effectively address these issues. It also helps to disentangle the role played by a specific economic phenomenon, that is internet use to acquire information, rather than considering multiple phenomena at the same time. Differently from existing works investigating the consequences of internet use diffusion (Guriev *et al.*, 2021), this paper goes a step further by shedding light on how different internet-based modalities to acquire information online can affect political trust and argues that the different risk of exposure to fake news that characterizes this internet-based modalities might explain the countervailing effect on political trust. Last, this paper adopts a country-specific perspective, which allows to limit the impact of cultural differences in explaining different level of political trust that is instead encountered when adopting a cross-country perspective. In so doing, it offers the first evidence in Italy on this important link. Hence, our paper merges two branches of the literature – the literature on political trust and its determinants and the literatures on the economics of internet and social media – and offers the following contributions. First, it documents the effects of the expansion of internet as a determinant of political distrust in Italy. Second, it shows that distinguishing among the different internet-based modalities to remain informed about political facts does matter, therefore analyses simply based on considering internet diffusion or single specific information manner can lead to misleading results. Third, it illustrates how the risk of fake news can play a role in this nexus. Fourth, it discusses how to limit the estimation bias of this relationship due to potential endogeneity by implementing the Lewbel method.

The rest of the paper is structured as follows. Section 1.2 provides a review of the background literature. It discusses the definition of political trust and its determinants (1.2.1), then it summarizes the main evidence on the political economy of internet and social media(1.2.2). Section 1.3 describes the data and the estimation methods adopted to carry out the analysis. Section 1.4 presents the results with related robustness checks to control for potential endogeneity issues. Section 1.5 concludes.

1.2 Background literature and testable hypotheses

1.2.1 Political Trust: definition and determinants

Trust is a multifaceted concept: It concerns beliefs and perceptions that others (people or institutions) will act consistently with their own expectations, thus fostering cooperation and collective actions (Ostrom & Ahn, 2009).

The introduction of the definition of trust in the economic literature dates back to the Nobel laureate Arrow (1972), suggesting that the absence of mutual trust poses a distinct challenge to economic systems, crucial for the success of collective endeavors. Trust plays a vital role in social cohesion; it is a fundamental ingredient in developing a vibrant civil society. It is also viewed as a mechanism for navigating complexity (Putnam *et al.*, 2001).

In the universe of papers that have explored the determinants and consequences of trust, the literature broadly distinguishes between two types of trust. The first form of trust is expressed with respect to other individuals in society (friends, members of the family, other known or unknown individuals), and it is also known as interpersonal, social (or generalized) trust. The second form is expressed with respect to different types of institutions (government, parliament, churches, universities, banks, etc. etc.). Within this form of trust, researchers often refer to political trust which specifically captures confidence toward the subgroup of governing institutions and public authorities.

Now, two approaches are used to explain political trust, one and the most diffuse approach, the so called performance approach, according to which political trust measures the extent to which governments deliver results that align with citizens' expectations as well as the extent to which government, its institutions, policymaking, and/or individual political leaders adopt behavior that are considered reliable, efficient, fair, and honest (Hetherington, 2005; Blind, 2007; Berg & Hjerm, 2010; Godefroidt *et al.*, 2015). Differently from the performance approach, another branch of the literature has introduced a social trust approach to explain political trust as an extension of interpersonal trust; the idea being that institutional trust represents a positive externality generated by interpersonal trust (Mishler & Rose, 2001; Suh *et al.*, 2012). Interpersonal trust fosters civic engagement and makes people more compliant with the rules imposed by public institutions (Guiso *et al.*, 2004; Tabellini, 2008).

So far, the increasing interest placed in political trust and its determinants has shed light on the role played by many different socio-economic factors, of which particular attention has been put on cultural background, government quality, corruption, and economic conditions. With respect to the role of culture, political trust has been proven to vary a lot between different countries, mainly due to differences in social, civic, and economic factors (Dijkstra *et al.*, 2020). Kaasa & Andriani (2022) show that the cultural context is significant in shaping trust in political institutions, as it can influence how citizens perceive public organizations and reinforce general distrust due to peer effects (since culture is a concept that operates at the societal level and manifests as a group phenomenon). In their work, they also demonstrate that power distance (i.e. the degree to which a society accepts an unequal distribution of power and hierarchical relationships) is inversely related to trust in institutions, meaning that more opportunities to influence public decisions may result in higher confidence toward national bodies. In relation to the role of unequal distribution of resources, attention has also been devoted to economic inequality and the mitigating channel represented by the digital interaction between citizens and public authorities (Palmisano & Sacchi, 2024). Furthermore, the literature has shed light on the concept of economic insecurity, considered a crucial determinant for the spread of populism and strictly related to political distrust in Europe (Guiso *et al.*, 2019, 2024; Ivanov, 2023). In a nutshell, trust toward government bodies has been proven as a mediator in the strong link between economic insecurity and populist votes.

Finally, among the main drivers of political distrust, the literature has placed great emphasis on the perception of institutional quality, crime, and corruption. Specifically, institutional quality has been depicted, among others, as one of the solutions to restore confidence toward institutional bodies, stressing the importance of transparency of the government bodies (Porumbescu, 2015)and public sector integrity (Van de Walle & Migchelbrink, 2022)). The perceptions of crime and corruption have instead been analyzed by Blanco & Ruiz (2013), who underline the negative association between crime and institutional confidence, and by Clausen *et al.* (2011), who focuses on the negative impact of government corruption on trust on a worldwide basis. The role of corruption has also been disentangled within national borders, with McAllister (2014) assessing the difference between perception and actual corruption in Australia and the more recent work by Daniele *et al.* (2023) focusing on the long-term impact of a large corruption scandal ("clean hands") in Italy. Specifically, they show that first time voters exposed to corruption scandals right before elections has had a long-term impact on both trust toward governments and voting preferences(Daniele *et al.*, 2023).

While the cited literature seems to agree on what the main drivers of institutional trust may be, there is still a general lack of consensus regarding how this variable should be properly measured and defined, especially considering the increasing number of surveys covering this topic.[4]

1.2.2 The political economy of internet and social media

In the last two decades, the understanding of the socio-economic impact of the digital revolution has come on top of researchers' and policymakers' agenda. Recent evidence suggests that while

[4]For instance, the topic is covered by surveys such as the World Value Survey or the European Social Survey (among others), asking participants question about how much they are confident toward their institutions (on scales from 0 to 10) taking into accounts different political bodies. Other works in the literature use voters turnout as a proxy of institutional trust (see Durante *et al.* (2024); Campante *et al.* (2018)

more connectivity can facilitate collective actions (Enikolopov *et al.*, 2020), internet and social media can also be used to spread extremist ideas and amplify harmful messages, potentially disrupting social cohesion and civic engagement (Antoci *et al.*, 2019; Geraci *et al.*, 2022).

Furthermore, the high-speed spread of contents and the newest form of online social interactions have drastically changed the nature and content of electoral campaigns, being now politicians able to receive immediate feedback and adjust their proposals. Consequently, the advent of internet has shaped the political playground both on the demand side (voters can access multiple sources of contents and information) and the supply side (representing an instrument for politicians to gain more attention), generating different effects on both voting participation and electoral choices.

With respect to electoral turnouts, the literature agrees that when considering the general exposure to internet access (measured by the broadband accessibility in a certain municipality) the increase availability of different contents online has played a crowding out effect, substituting political interest with the consumption of entertainment contents. Consequently, internet has been found to decrease voting participation, with such effect been proven for many mature democracies including Germany (Falck *et al.*, 2014), England (Gavazza *et al.*, 2019) and Italy (Campante *et al.*, 2018). At the same time, with political actors adapting to the newest way of interactions with the electorate, the effect of the general Web on political behaviors has been identified as a factor benefiting anti-establishment parties, able to mobilize disenchanted voters (Donati, 2023) and to alter the electoral tendencies in favor of populist politicians (Schaub & Morisi, 2020). These findings seem to agree that internet and social media have been the vehicle for European countries to have less but more polarized voters, favoring particularly populist parties.

With the spread of populism being linked to political distrust in many different papers (Algan *et al.*, 2017; Guiso *et al.*, 2024), we argue that social media could have additionally disrupted political legitimacy, something the literature have only recently started to address. Guriev *et al.* (2021) point specifically at the link between internet speed and confidence toward national government. In their analysis, they exploit the worldwide implementation of fast internet between 2008 and 2017 to test the impact of higher information availability on confidence in national governments, finding a strong negative relationship when internet is not censured. The mechanism, they argue, rely on the fact that the free-online media market could result into higher knowledge of misgovernance, higher perception of corruption, higher exposure to false information and, finally, to undermine political legitimacy. Our contribution differs from these previous works mainly in two respects.

First, given that the cultural and institutional context strongly affect political trust as discussed in Section 1.2.1, we endorse a national perspective and explore the association between government trust and online information acquisition within a single country setting, namely the Italian setting, country in which the determinants of political trust and especially the impact of information acquisition on trust remains largely unexplored. In fact, while there is a flourishing literature on the effect of the diffusion of broadband implementation on social capital in Italy (Putnam *et al.*, 1994; Campante *et al.*, 2018; Durante *et al.*, 2024), not much is known about how the use of internet to be informed about political facts may affect political trust.

Second, our paper goes beyond the hypotheses investigated by the previous literature and, in addition to consider the effect of internet use, it makes light on how different modalities of acquiring specific information online can exert a different impact on trust toward national authorities and political parties. Thus, revealing that limiting the analysis to considering internet use only would just capture an average effect and hide a more complex underlying nexus between information acquisition and political trust. The newest forms of interactions have, in fact, a crucial difference with respect to traditional media, since individuals are at the same time consumers (as with TV and traditional newspapers) and providers of information (Campante *et al.*, 2018; DellaVigna & La Ferrara, 2015). In this demand-supply process of information and contents, social media differ from traditional means with respect to two additional critical aspects: the presence of very low entry barriers and the possibility of benefiting from the consumer's "profiling" [5] (Zhuravskaya *et al.*, 2020). With respect to the former, evidence shows that the increasing number of online sources may threaten the integrity of information quality, originally maintained by traditional media's reputation systems, enabling the diffusion of unfiltered news at higher speed (Cagé, 2020; Gentzkow & Shapiro, 2006). Social media have been proven the instrument for false and misleading news to spread more rapidly both on Twitter (Vosoughi *et al.*, 2018) and Facebook (Allcott & Gentzkow, 2017), with the magnitude of political consequences still unclear [6] .

In tandem, social networks and their ad-personam algorithms have been proven to increase homophily and creating "echo chambers" (Gentzkow & Shapiro, 2011), with the implication of having citizens less exposed to those contents that are different from their pre-existing biases and increase political polarization (Levy, 2021). For these reasons, we argue that the use of different modes of acquiring political information could affect trust toward national governing authorities differently.

1.2.3 Hypotheses

The discussion of the background literature in the previous sections brings us to hypothesize that there exists a relationship between internet use to acquire political information and trust toward political institutions. At the same time, we remain agnostic on its sign, as it may depend on which specific internet-based modality is used to get this information.

On the one hand, online newspapers help in overcoming traditional constraints such as resources, time, and space, but still maintaining a top-down approach to the dissemination of online information, which mirrors the one-way communication style of offline media. Information providers through online newspapers typically aim to retain control over publication and view the audience primarily as passive recipients with limited space for user-generated content or alternative viewpoints, resulting in minimal influence of public discourse. The information

[5] Profiling on social media refers to the practice of collecting and analyzing user data to create detailed profiles of their characteristics and behaviors. In this context, such activity may increase individual exposure toward certain topics confirming pre-existing biases

[6] The "Cambridge analytica" scandal happened during the 2010s is a clear example.

available on online news websites remains subject to mediation and influence by editors and political elites, who may skew news coverage to align with their interests and garner support for established institutions and the democratic regime.

Moreover, unlike social media platforms, newspapers operate under clear legal and professional responsibilities regarding the content they release. This accountability framework makes them less inclined to disseminate fabricated or misleading information, since reputation costs and legal consequences act as strong disincentives. Therefore, it is plausible to expect that consuming information from news media websites will contribute to political trust, given the overall pro-system bias of these sources.

On the other hand, the interactive nature of social networking sites fosters participation and peer-to-peer dialogue and revert the communication approach from top-down to bottom-up approach. Social media platforms facilitate the production of user-generated content and information sharing, without the established hierarchy characteristic of traditional media. They offer equitable access to news production and consumption, reducing the elite bias present in traditional media. Their unfiltered nature can reshape individuals' exposure to information, facilitating direct access to news shared among peers without the mediation of news corporations. Citizens are more likely to encounter marginalized perspectives and anti-establishment arguments, which could potentially undermine their confidence.

Hence, we will first test whether a link exist between political trust and internet use to get political information, treating it as a "black box", thus not distinguishing between different internet usages. More specifically, we will compare the effects on political trust of getting information from the web (in general) with those of getting information from more traditional means (namely television, radio, newspapers and so on), and ultimately with those not consuming any information about politics at all. Then, we will test whether different online modalities for political information consumption impact political trust differently. That is, we will compare the effect of information consumed via social networks and the effect of information consumed via online newspapers with the effect of information consumed using traditional offline means.

1.3 Data and Methods

Most of the cited literature regarding political trust focuses on between-countries comparisons, exploiting their institutional and cultural differences, but such concept can also show some heterogeneity within national borders (Kaasa & Andriani, 2022; OECD., 2022). Hence, this paper focuses on a single county – namely, Italy – which presents interesting features. Italy is a country historically characterized both by a strong and long-lasting political instability (since 2008 none of the government in place lasted for the whole five-year mandate), which may have further contributed to weaken the relationship between citizens and institutions and to reduce their confidence. Moreover, this country was among the first to directly experience the pandemic in Europe, with the COVID19 disease reaching more than 10 million cases between 2020-2021.

To test our research hypotheses, we use data extracted from the "Multi-purpose Survey on Families: Aspects of Daily Life", a sample survey conducted annually by ISTAT since 1993, aimed at analyzing Italian citizens' habits, the problems they face and how much they are satisfied with the functioning of those utilities that should be built to improve the quality of life. The survey is conducted on a nationally representative sample of 25,000 households.

Among the different topics investigated, we extract for our purpose the ones related to political trust and the different means of political information, as well as a number of individual characteristics that we use as controls in our analysis.

To capture political trust, our dependent variable, we use the answers interviewed give to the following question: "Using a score of 0 to 10 indicate how much you trust the following institutions, where 0 indicates no trust at all and 10 indicates full trust: National government/ regional government/ municipal government /political parties."
Figure 1.1 reports the country average level of trust toward the four different institutions considered – national government, regional government, municipal government, political parties – between 2014 and 2022. The time trend of trust toward the national government has followed a particular path, being slightly recovering after years of decline starting from 2018. However, Italy has been experiencing a massive level of government distrust, with an average score never above 5. These low levels are a warning sign of the political crisis in this country. The situation does not improve when we consider trust toward the other mentioned institutions, namely the regional and municipal government, and political parties. In particular, the latter has registered the lowest scores of trusts, but neither regional nor municipal government reach sufficient levels. The results presented above refer to the national level, yet Italy is characterized by marked territorial disparities. In light of the well-known North–South divide, we also adopt a territorial perspective, graphically illustrated in Figures 1.2 and 1.3.

The literature on the historical roots of this divide highlights the persistence of higher levels of social capital in the Northern regions, while the South, shaped by the legacy of the Bourbon rule, exhibits lower levels of social trust, civic engagement, and cooperation (Bigoni *et al.*, 2016; Felice, 2018; Putnam *et al.*, 1994). These findings are broadly confirmed when considering sub-national institutions (see Figure 1.3). However, an intriguing pattern emerges with respect to trust in the national government: contrary to expectations, Southern regions appear to display slightly higher levels of confidence in this national institution compared to their Northern counterparts (Figure 1.2).

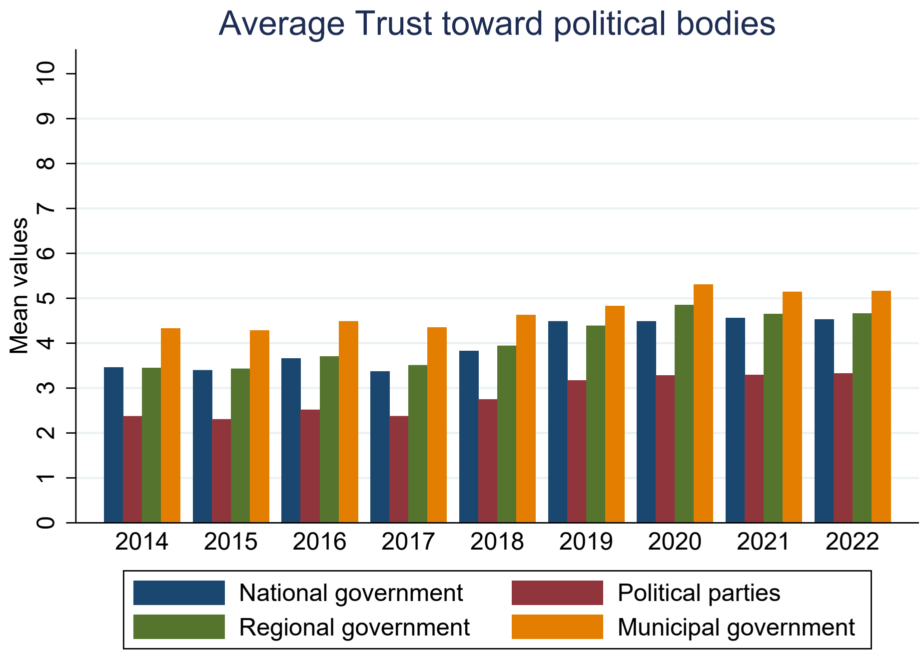

Figure 1.1: *Average trust toward different institutions in Italy, 2014-2022. Source: Authors' elaboration on ISTAT (2014-2022).*

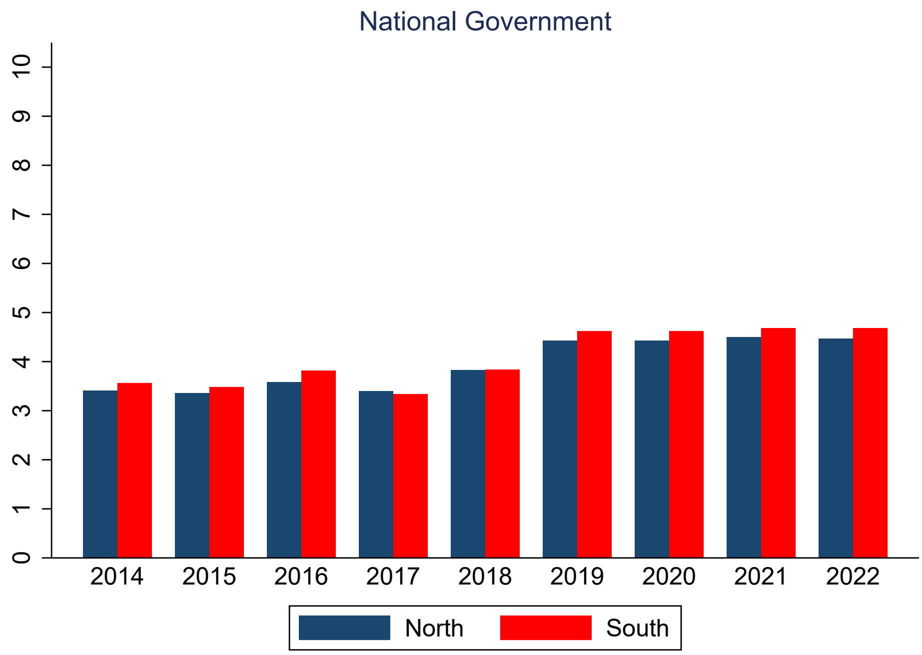

Figure 1.2: *Average trust toward national government in Italy: North-Centre vs South, 2014-2022. Source: Authors' elaboration on ISTAT (2014-2022).*

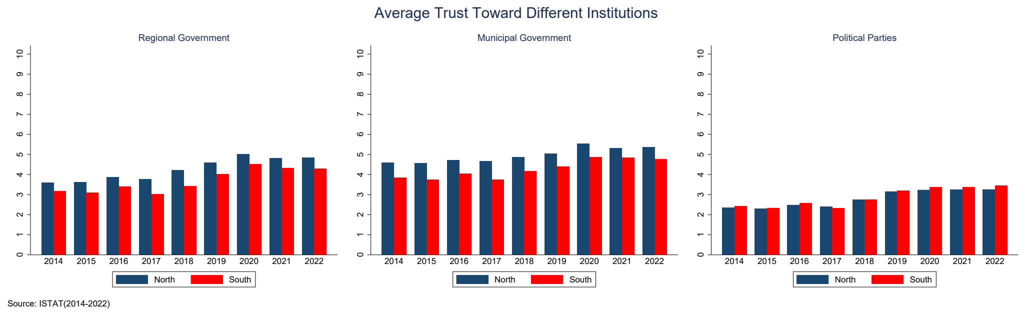

Figure 1.3: *. Average trust toward regional government, Municipal government, Political Parties: North-Center vs. South, 2014-2022 . Source: Authors' elaboration on ISTAT (2014-2022).*

As trust in one authority is often strongly correlated with trust in others, we construct an index of *political trust* using Principal Component Analysis (PCA).[7] PCA is a statistical method that combines information from several observed variables into a smaller set of synthetic variables, called principal components, by exploiting their shared variance (Greenacre *et al.*, 2022). This approach has been widely applied in the empirical literature on social capital and institutional trust (see, among others, Kaasa & Andriani, 2022; Durante *et al.*, 2024).

In our case, PCA allows us to combine the different items of political trust into a single index. The first component explains about 75% of the total variation across the four indicators (Table 1.1). Figure 1.4 confirms this result: only the first component has an eigenvalue larger than one, which justifies retaining it as our synthetic measure.

Table 1.1: *PCA for political trust*

Component	**Eigenvalue**	**Difference**	**Proportion**	**Cumulative**
Comp1	3.01308	2.53162	0.7533	0.7533
Comp2	0.481463	0.189592	0.1204	0.8736
Comp3	0.291871	0.0782873	0.0730	0.9466
Comp4	0.213583		0.0534	1.0000

Source: Authors' elaborations based on ISTAT, 2014-2022.

[7]For robustness checks, we also replicate the analysis using trust toward the national government and, separately, toward all the other authorities; results are reported in the Appendix.

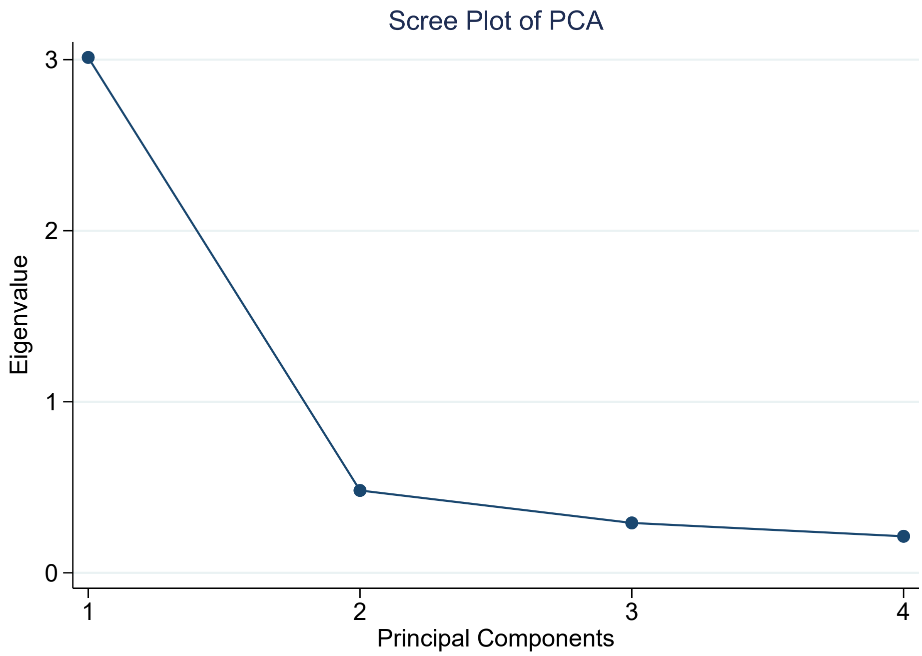

Figure 1.4: *Scree plot of the PCA of political trust. Source: Authors' elaboration on ISTAT (2014-2022)*

Table 1.2: *Loadings and Components of Political Trust. Source: Authors' elaborations based on ISTAT, 2014-2022.*

Variables	**Comp1 (Loadings)**
Trust: *National Government*	0.5100
Trust: *Political Parties*	0.4922
Trust: *Regional Government*	0.5252
Trust: *Municipal Government*	0.4710

The loadings of the variables (Table 1.2) are all positive and of similar magnitude (around 0.50), indicating that trust in the national government, political parties, regional government, and municipal government contribute almost equally to the latent dimension we label as *political trust*.[8]

As for the main explanatory variable, political participation through different information means is instead extracted by the question: "how do you get information about politics?". The interviewed can choose between formal traditional means, such as television, newspapers and the radio or informal means (friends, family and colleagues). Moreover, participants to the survey are asked whether they get political information from the web, with the possibility to distinguish between online newspapers and social networks.

[8]In simple terms, this index assigns higher values to individuals who report high trust in all these institutions, and lower values to those who report low trust across the board.

For the analysis, we therefore exploit these differences in modalities by constricting three dummy variables. The first dummy variable distinguishes individuals that use internet for the acquisition of political information from those that do not use this modality; it takes value 1 if the individual uses internet (not distinguishing between the different modalities, hence using either social media or online newspaper or both) and 0 otherwise. The second and third dummy variables further distinguishes individuals by the internet modality used to get information. One dummy variable takes value 1 is the individual only uses social networks and 0 otherwise. The other takes value 1 is the individual only uses online newspaper and 0 otherwise. We add to our analysis the usual controls, hence including variables about age, gender, region of residence, education levels, occupation, marital status and family size. To check for potential confounders, we also include variables about individual economic satisfaction and self-reported health status, the frequency of internet use, and feelings regarding the crime rate in the living area. These variables are all described in Tables 1.11 and 1.11.b in the Appendix.

Hence, we proceed with the estimation of the following OLS model.

$$Y_i = \beta_0 + \beta_1 P_i + \beta_2 X_i + \gamma_t + \delta_r + \epsilon_i \tag{1.1}$$

Where the dependent variable Y_i is the PCA of trust toward the mentioned institutions, P_i being the means to get political information, and X_i the mentioned set of covariates to control for unobservable, ϵ_i is the error term (we use heteroskedasticity-robust standard errors). For robustness purposes, we also estimate equation 1.1 through ordered probit when the dependent variable is represented by trust in the national government, results of which we show in the appendix (table 1.12).

1.4 Empirical analysis

1.4.1 Baseline results

Table 1.3 reports the main results. Column (1) shows the results of estimating equation 1.1 using OLS and adopting a parsimonious specification, where only the variable "Internet Use" (together with region and year fixed effects) is used as explanatory variable. We add all controls in columns (2), representing the most comprehensive specification. In these columns, the outcome variable used is the composite indicator obtained through the PCA. Columns (3) provide estimations of equation (1) when adopting trust in national government as outcome variable.[9]

It clearly appears that our first hypothesis is supported by the data: we find a significant relationship between political trust and internet use to get political information. Moreover, it seems that individuals obtaining political information online tend to trust institutions less than individuals getting this information offline through more traditional means. This finding is robust and statistically significant across columns. Thus, it can be inferred that the effect of being an 'online consumer' of political content is one of the negative determinants of the recorded political trust, a result that is consistent with previous findings of that branch of the

[9] in table 1.13 in the Appendix we also show the results of our model when the dependent variable is trust toward the other institutional bodies considered for the construction of our PCA, namely *Political parties*, *Regional* and *Municipal government*

literature pointing to a negative effect of internet diffusion on trust.

As for the control variables, we observe a negative association between trust and poor education level, while the coefficient associated to individuals with tertiary degree show a positive sign with respect to individuals with high school diploma. Arguably, this might happen as more educated individuals could benefit more from political processes, getting better jobs and life chances. Moreover, more educated individuals might play a role in politics and therefore develop more political trust while less educated individuals are alienated (Turper & Aarts, 2017)[10]. Not surprisingly, a negative association arises between trust and perceived risk of crime in the living area, while trust is positively associated with self-reported health status and economic satisfaction. Increase in family size instead makes people less confident with respect to the ruling actors, with that couples with babies being among the ones trusting less.

Table 1.3: *Internet use and political trust, 2014–2022*

	(1)	(2)	(3)
	OLS	OLS	OLS
VARIABLES	Pol. trust	Pol. trust	National gov.
Use of internet	-0.146***	-0.0658***	-0.134***
	(0.00614)	(0.00819)	(0.0126)
Gender		-0.00998	0.0221**
		(0.00679)	(0.0106)
Age: 14–24		0.178***	0.280***
		(0.0142)	(0.0218)
Age: 45–64		0.123***	0.340***
		(0.00889)	(0.0137)
Age: over 65		0.239***	0.507***
		(0.0135)	(0.0209)
Education: Primary		-0.0258***	-0.156***
		(0.00809)	(0.0125)
Education: Tertiary		0.133***	0.339***
		(0.00948)	(0.0147)
Labour market status: inactive		0.0198	0.0629***
		(0.0142)	(0.0218)
Labour market status: occupied		-0.135***	-0.179***
		(0.0129)	(0.0199)
Family size: No family		0.0579***	0.0512***
		(0.00960)	(0.0149)

[10]Note that another branch of the literature argues that increased education decreases political trust as an increase in education levels should increase the citizens' expectations in terms of government performance. More educated people are more aware of what should be the role of institutions that represent their interests and possess more tools to identify potential or existing problems and shortcomings in the public institutions' conduct.

VARIABLES	(1) OLS Pol. trust	(2) OLS Pol. trust	(3) OLS National gov.
Couple w/o children		-0.0271***	-0.0557***
		(0.00937)	(0.0146)
Single parent		0.0118	0.0173
		(0.0116)	(0.0179)
Health: No good/bad		0.106***	0.143***
		(0.0153)	(0.0239)
Health: Good		0.217***	0.298***
		(0.0153)	(0.0239)
Economic sat: not very		0.586***	0.856***
		(0.0119)	(0.0185)
Economic sat: enough		0.980***	1.417***
		(0.0118)	(0.0183)
Economic sat: good		1.100***	1.585***
		(0.0205)	(0.0318)
Crime rate: not very		-0.0816***	0.0180
		(0.00814)	(0.0127)
Crime rate: quite		-0.301***	-0.243***
		(0.00989)	(0.0154)
Crime rate: a lot		-0.579***	-0.594***
		(0.0153)	(0.0239)
Internet freq: daily		-0.147***	-0.206***
		(0.00889)	(0.0137)
Region FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	247,269	234,820	235,888
R-squared	0.061	0.113	0.102

Notes: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include a constant term as well as region and year fixed effects, though their coefficients are not reported in the table. The omitted (reference) categories are: Offline- TV, radio, newspapers- traditional means (Use of internet), Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022).

Two results deserve more attention. The first concerns the link between trust and the frequency of internet use, as daily users seems to trust institution less then those that use it sporadically. The second concern the association between political trust and the age of the respondent, which shows that individuals with age between 25 and 44 years old (our reference class) are the ones who trust institutions less. Interestingly, such age cohort encompasses those citizens who were in their "impressionable years" when the "clean hands" scandal exploded and took over the Italian public debate back in 1992-1994. Hence, our results signal the existence of a long-term impact of corruption and crime on institutional trust (see also on this Daniele *et al.* (2023)). Both results are better addressed in section 1.4.2.

Here, a point is in order. The answer to the question of whether the interviewee uses the internet to get informed about political facts contains many missing values. We therefore replicate the main analysis reported in Table 1.3 on the extended sample that includes individuals with a missing answer to that question, interpreting this missing value as capturing those individuals who do not get informed at all, as implied by the structure of the questionnaire.

Table 1.4: *Online vs. offline vs. not informed at all*

VARIABLES	(1) OLS PCA	(2) OLS PCA	(3) OLS National gov.
Offline Means	0.133***	0.0467***	0.105***
	(0.00692)	(0.00786)	(0.0121)
Not at all	-0.168***	-0.197***	-0.251***
	(0.00821)	(0.00952)	(0.0145)
Controls	NO	YES	YES
Region FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	335,466	315,960	317,515
R-squared	0.043	0.109	0.097

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The constant, region and year fixed effects are included but their coefficients are not reported in the table. Reference group: Use of internet to get political information. Source: author's elaboration from ISTAT (2014-2022).

Hence, we recode our main explanatory variable (the information mean) into a categorical variable with three modes: 'getting information online' (our reference category), 'getting information offline,' and 'not getting information at all' (if missing value). The estimates reported in Table 1.4 corroborate our previous results, which refer to the different effects on political trust of the different ways of obtaining political information. Indeed, compared to getting information online, people who get information offline tend to feel more confident about political institutions. Moreover, table 1.4 adds two interesting pieces of information to this framework. First, ignorance about facts with political content is always detrimental to political trust. Second, the Internet is not always bad for political trust. Compared to individuals who do not get information at all, the use of the Internet to acquire political information can improve confidence in political institutions. On the one hand, media negativity, coupled with its portrayal of politics as a competitive race, fosters cynicism and a sense of malaise, ultimately eroding trust in political institutions. On the other hand, exposure to media can create a positive cycle, enhancing civic engagement, political interest, and trust in government. Hence, the Internet is an instrument that can be adequately and potentially used to strengthen political trust, especially for those citizens who do not usually consume information about political facts.

We move a step forward to test our second hypothesis, trying to assess how this negative sign of the internet news consumption can be driven by the different means people can use within the web, namely newspapers and streaming contents or social networks. We therefore construct two different dummy variables, with the aim of capturing, from one side, the effect of consuming information through social networks such as Facebook, Twitter and Others, and, from the other side, the effect of using the internet to read information through traditional newspapers and television in their digital form. Hence, the first dummy ("Social networks") will take the value of 1 if the individual use social networks and 0 if not, while the second dummy ("Online newspapers") will take the value of 1 if the individual consume information on online newspapers and 0 otherwise. The effect we aim to isolate builds on the evidence, as suggested by the cited literature (Zhuravskaya *et al.*, 2020; Allcott *et al.*, 2020, among others), that newspapers may still provide more pro-government (or pro-party) content than social networks. The latter, through their algorithms, tend to prioritize the most divisive material and thereby amplify political polarization (Azzimonti & Fernandes, 2023). In addition, newspapers must also consider the costs of losing credibility ("reputation costs"), which gives them stronger incentives to engage in fact-checking. Results are reported in table 1.5 and 1.6. As expected, it seems that social networks use to get political information is the main driver of the negative link with political trust, with negative and statistically significant sign. On the other hand, online newspapers and digital television exert a positive, though comparatively smaller, effect, indicating a link between trust and the consumption of more balanced and pro-government news sources. We also take into account the possibility to consume information from both kind of sources jointly, negative sign of which underline the negative effect coming from the Social networks use.

Table 1.5: *OLS results on the PCA of Political Trust*

VARIABLES	(1) OLS PCA of Trust	(2) OLS PCA of Trust	(3) OLS PCA of Trust	(4) OLS PCA of Trust
General Web	-0.0658***			
	(0.00819)			
Social Networks		-0.145***		-0.211***
		(0.00912)		(0.0127)
Online Newspapers			0.0318***	0.0137
			(0.00831)	(0.00978)
Both Means				-0.0720***
				(0.0123)
Controls	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	234,820	234,820	234,820	234,820
R-squared	0.113	0.114	0.113	0.115

Note: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include a constant term as well as region and year fixed effects, though their coefficients are not reported in the table. The omitted (reference) categories are: Offline- TV, radio, newspapers- traditional means (Use of internet), Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022).

Table 1.6: *Results of Different Means on Trust Toward National Government*

VARIABLES	(1) OLS National Gov.	(2) OLS National Gov.	(3) OLS National Gov.	(4) OLS National Gov.
General Web	-0.134***			
	(0.0126)			
Social Networks		-0.306***		-0.413***
		(0.0142)		(0.0197)
Online Newspapers			0.0543***	0.0337**
			(0.0129)	(0.0151)
Both Means				-0.178***
				(0.0191)
Controls	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	235,888	235,888	235,888	235,888
R-squared	0.102	0.103	0.102	0.104

Note: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include a constant term as well as region and year fixed effects, though their coefficients are not reported in the table. The omitted (reference) categories are: Offline- TV, radio, newspapers- traditional means (Use of internet), Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022).

As in the previous paragraph, we take into consideration the existence of people who do not get information at all. We therefore divide the variable into categories to distinguish between getting information through social networks or online newspapers, doing so offline, or not getting information at all. Hence, we now have a variable with five categories: "not getting information at all," "information through social networks," "information through online newspapers", their joint use, and "information through traditional means" (which we take here as our reference category). The estimates reported in Table 1.7 confirm the previous results. When adding our controls (column (2)), we find once again that individuals who do not get information at all display lower levels of trust in institutions. Moreover, when considering the population of citizens who do not read any information, we again observe that getting information online does not always have a negative effect: obtaining news from online newspapers still shows a positive and statistically significant coefficient compared to traditional means. By contrast, getting information through social networks, as well as the joint use of both online modalities, continues to exert a strong negative effect on political trust.

Table 1.7: *Online vs. Offline vs. Not Informed*

	(1)	(2)	(3)
	OLS	OLS	OLS
VARIABLES	Pol. trust	Pol. trust	National government
Not at all	-0.301***	-0.249***	-0.365***
	(0.007)	(0.008)	(0.012)
Online Newspapers	-0.014	0.037***	0.072***
	(0.009)	(0.010)	(0.015)
Social Networks	-0.352***	-0.196***	-0.392***
	(0.012)	(0.012)	(0.019)
Both means	-0.153***	-0.056***	-0.153***
	(0.011)	(0.012)	(0.019)
Controls	NO	YES	YES
Region FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	335,466	315,960	317,515
R-squared	0.045	0.110	0.098

Note: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include a constant term as well as region and year fixed effects, though their coefficients are not reported in the table. The omitted (reference) categories are: Offline- TV, radio, newspapers- traditional means (Use of internet), Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022).

We want to better understand the mechanisms behind these results. To do so, we first restrict the sample to individuals who declare using the Internet to get information about politics, in order to assess whether there are differences in trust behavior between social network users and online newspaper readers. By doing so, we hence compare only those who are online political information users, excluding from the analysis individuals who rely solely on traditional means or who do not get information at all. Table 1.8 shows that, relative to people who use both sources jointly (reference category), exclusive reliance on social networks is strongly and significantly associated with lower political trust, both in terms of the PCA index (columns (1)–(2)) and confidence in the national government (column (3)). By contrast, exclusive reliance on online newspapers is associated with a positive and statistically significant effect across all specifications. This suggests that the informational environment provided by online newspapers is closer to that of traditional offline media, while social networks exert a distinctly negative influence on institutional trust. The joint use of both modalities, taken as the baseline, lies in between: compared to this group, online newspapers alone increase trust, whereas social networks alone depress it.

Table 1.8: *Within the web analysis: social networks vs. newspapers online on the web*

	(1)	(2)	(3)
	OLS	OLS	OLS
VARIABLES	PCA of Political trust	PCA of Political trust	National government
Online newspapers	0.126***	0.0806***	0.204***
	(0.0129)	(0.0131)	(0.0205)
Social networks	-0.194***	-0.147***	-0.252***
	(0.0154)	(0.0154)	(0.0241)
Controls	NO	YES	YES
Region FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	89,914	85,984	86,234
R-squared	0.065	0.120	0.117

Note: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include a constant term as well as region and year fixed effects, though their coefficients are not reported in the table. The omitted (reference) categories are: both modalities used jointly, Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Sample is based on individuals using online platforms to get information about politics. Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022).

Overall, these findings reinforce the idea that not all forms of online information consumption have the same consequences. Online newspapers seem to replicate the dynamics of traditional media, where the flow of information is mediated by political elites and contributes to sustaining democratic support and political trust. In contrast, the unmediated and user-driven environment of social networks facilitates the spread of alternative and often polarized content, which undermines trust in political institutions. As discussed in Section 1.2.2, the former context reflects a top-down process of communication, with individuals mainly acting as consumers of professional news (DellaVigna & La Ferrara, 2015; Campante *et al.*, 2018), while the latter is a bottom-up environment where individuals are both consumers and producers of content, with a clearly different—and often negative—impact on political trust.

Then, to better understand why the effects of different Internet modalities on political trust point in opposite directions, we exploit our dataset once more by considering respondents' perceptions about the likelihood of having read fake news online. This variable is available only in the last wave of the survey, but it provides valuable information to assess whether exposure to misinformation differs across Internet-based channels of political information. In particular, we test whether the probability of encountering fake news varies between individuals who rely on social networks and those who rely on online newspapers.

Table 1.9: *Information Source and Fake News Exposure*

	(1)	(2)	(3)
	Probit	Probit	Probit
VARIABLES	Fake News	Fake News	Fake News
Social networks	0.412***		
	(0.0257)		
Online newspapers		-0.0493	
		(0.0313)	
Only Social networks			-0.291***
			(0.0371)
Only Online newspapers			-0.539***
			(0.0306)
Gender (Female)	-0.124***	-0.0988***	-0.120***
	(0.0256)	(0.0255)	(0.0257)
Age 14-24	0.169***	0.214***	0.165***
	(0.0513)	(0.0506)	(0.0513)
Age 45-64	-0.214***	-0.272***	-0.210***
	(0.0304)	(0.0300)	(0.0305)
Age 65+	-0.328***	-0.398***	-0.323***
	(0.0533)	(0.0528)	(0.0535)
Primary Education	-0.0983***	-0.0779**	-0.0752**
	(0.0342)	(0.0340)	(0.0343)
Tertiary Education	0.125***	0.0951***	0.107***
	(0.0294)	(0.0293)	(0.0296)
Inactive (Not Working)	0.0345	0.0259	0.0250
	(0.0526)	(0.0520)	(0.0526)
Employed	0.0563	0.0471	0.0490
	(0.0458)	(0.0454)	(0.0459)
No Family	0.0150	0.0109	0.0194
	(0.0370)	(0.0367)	(0.0371)

VARIABLES	(1) Probit Fake News	(2) Probit Fake News	(3) Probit Fake News
Couple w/o Children	-0.0172	-0.0155	-0.0142
	(0.0366)	(0.0365)	(0.0367)
Single Parent	0.0409	0.0444	0.0394
	(0.0410)	(0.0407)	(0.0411)
Poor/Bad Health	-0.0511	-0.0808	-0.0492
	(0.0787)	(0.0780)	(0.0788)
Good Health	-0.152**	-0.175**	-0.153**
	(0.0764)	(0.0758)	(0.0766)
Low Economic Satisfaction	-0.0815*	-0.0896*	-0.0765
	(0.0482)	(0.0477)	(0.0482)
Medium Economic Satisfaction	-0.151***	-0.188***	-0.151***
	(0.0457)	(0.0452)	(0.0457)
High Economic Satisfaction	-0.115*	-0.144**	-0.122*
	(0.0648)	(0.0642)	(0.0650)
Low Crime Perception	0.0950***	0.0868***	0.0917***
	(0.0291)	(0.0289)	(0.0292)
Medium Crime Perception	0.0587	0.0621	0.0561
	(0.0401)	(0.0397)	(0.0401)
High Crime Perception	-0.00905	-0.00878	-0.0126
	(0.0692)	(0.0687)	(0.0693)
Daily Internet Use	0.443***	0.465***	0.429***
	(0.0499)	(0.0497)	(0.0500)
Region FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	11,403	11,403	11,403

Note: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include a constant term as well as region and year fixed effects, though their coefficients are not reported in the table. The omitted (reference) categories are: Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Sample is based on individuals using online platforms to get information about politics. Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022).

Table 1.9 shows that the use of social networks is positively and significantly associated with declaring to have encountered fake news (column (1)), while online newspapers show no significant effect (column (2)). When distinguishing between exclusive and joint use (column (3)), both “only social networks” and “only online newspapers” are associated with a lower probability of reporting fake news, compared to individuals who combine the two sources. This suggests that the overlap of the two modalities amplifies the perception of encountering misinformation, as the negative effect of joint use appears to be mainly driven by social networks, which outweigh the role of online newspapers and shape the overall exposure to fake news.

1.4.2 Robustness checks

To strengthen our findings, we conduct a series of robustness checks. A first dimension of heterogeneity is territorial: given the historical North–South divide that characterizes Italy and is evident in economic indicators such as GDP, employment, innovation, and infrastructure, we interact Internet use with dummies distinguishing North–Center from South (Figures 1.1 and 1.2). As reported in Table 1.14 in the Appendix, the negative association between general Internet use and political trust is confirmed and appears more pronounced in the South compared to the North–Center. When focusing on specific modes of use, the detrimental effect of social networks is consistently negative and does not display significant territorial variation. In the case of online newspapers, however, the positive association detected in the North–Center does not hold uniformly: it weakens in the South and turns slightly negative, suggesting that territorial heterogeneity plays a role in shaping how different online information sources relate to political trust.

We also examine age differences, since the shift from offline to online information is largely part of a generational transition. To this end, we interact Internet use with four age groups (15–24, 25–44, 45–64, 65+), as shown in Appendix Table 1.15. The negative association between Internet use and political trust is confirmed across groups, but it tends to be stronger among younger respondents, while it is less pronounced among older cohorts. Social networks consistently show a negative effect on trust, with some evidence that the association is more detrimental among the youngest and, to a lesser extent, the elderly. For online newspapers, the picture is more mixed: the overall association is weak, but it appears somewhat more favorable among middle-aged respondents.

A further source of heterogeneity concerns the intensity of Internet use. Appendix Table 1.16 explores this dimension by interacting online information with different frequencies of access. More frequent Internet users tend to report lower levels of trust overall, irrespective of the mode of use. The interaction terms indicate that frequency does not significantly modify the negative association of general Internet use, while for social networks the effect appears somewhat attenuated among heavy users. With respect to online newspapers, the association remains broadly stable across different usage intensities.

Overall, these three patterns suggest that the association between Internet use and political trust is generally robust: for general Internet use, differences across groups concern mostly the intensity rather than the direction of the link, with stronger effects among the young and in the South; when exploring different information modalities, the negative association with social networks emerges consistently across contexts, while for online newspapers some meaningful variation appears, especially across age groups and between North–Center and South. By contrast, no substantial heterogeneity emerges when considering the frequency of Internet use.

To further support our findings, we also replicate our main analysis focusing on the different years of the survey. In particular, we argue that the relationship between political trust and online information may be strongly driven by the historical moment we are considering, especially recalling the potential role that elections, political and socio-economic shocks could have played during the years of our analysis.

With respect to that, we provide graphical evidence of the relationship between different types of internet use and political trust over time. Figure 1.5 displays the pattern of our main coefficient (the use of Internet in general), which we analyze in the different years between 2014-2022. As shown, we can see how the trend remains negative for most of our time span, further supporting the hypothesis of a detrimental effect of online information use on political trust.

Such conclusion holds with some exceptions, namely the first two years of the analysis, with the main coefficient positive but non-statistically significant, and curiously in 2020, where the coefficient is non-significant after years of slight increase. We also recall the subsequent fall in the two years after the pandemic, with graphical evidence reported in figures 1.6 and 1.7.

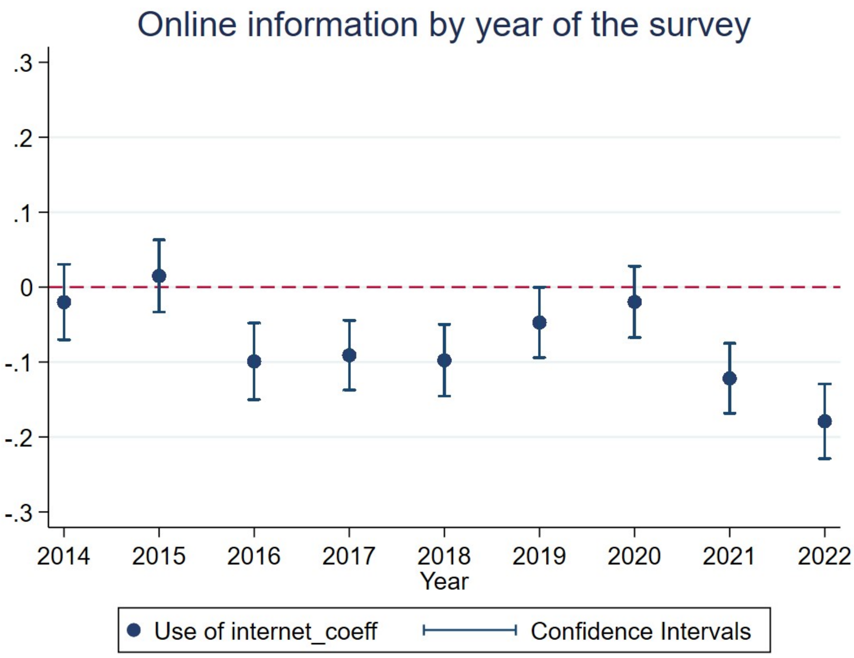

Figure 1.5: *Political trust and online information by the year of the survey. For all the coefficients estimated, controls have been included. Source: our elaboration from ISTAT (2014-2022).*

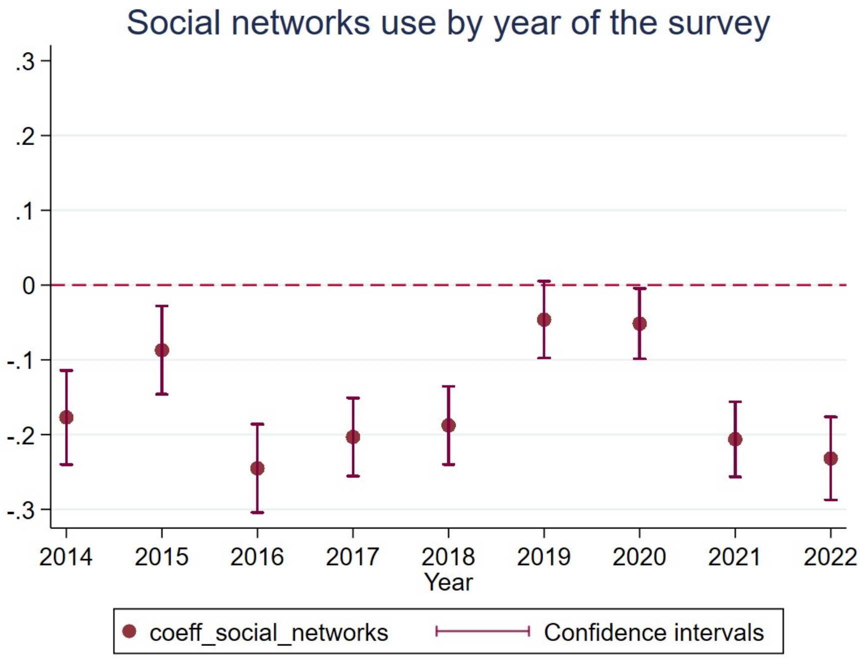

Figure 1.6: *Political trust and online information through Social Networks by the year of the survey. For all the coefficients estimated, controls have been included. Source: our elaboration from ISTAT (2014-2022).*

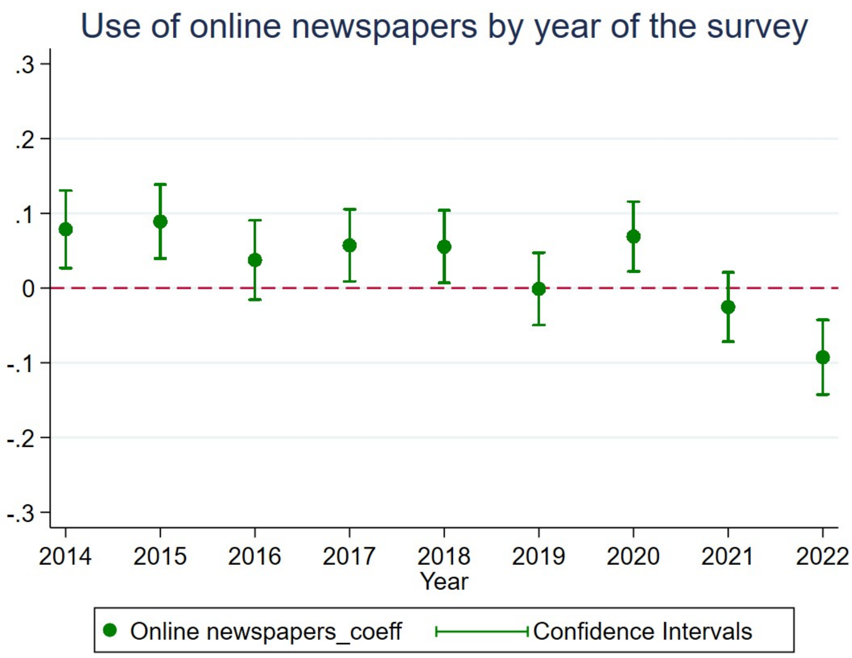

Figure 1.7: *Political trust and online information through Online newspapers by the year of the survey. For all the coefficients estimated, controls have been included. Source: our elaboration from ISTAT (2014-2022).*

Figure 1.6 reports the coefficients of that relates social networks to political trust. We here notice that this sign is always negative and statistically significant throughout all our time span, providing additional support to our analysis with respect to the role that social networks have played.

Figure 1.7 presents the coefficients that track the relationship between the use of online newspapers and political trust over time. These coefficients are consistently positive but show fluctuations, which could serve as a potential warning sign. Notably, we observe a negative shift in the coefficients for online newspapers following the 2020 wave. This warning sign could arguably be a symptom of the "infodemic" and its impact on the relationship between political trust and internet usage.

1.4.3 Endogeneity

The results just commented leave space for many considerations. However, as often in econometrics, their causal interpretation require caution due to the possible presence of endogeneity in our model.[11] The link between the mode of information acquisition and political trust may be affected by both omitted variable bias, with underlying factors such as personality traits, political preferences, or daily direct experience with government inefficiency, and reverse causality, with individuals who already distrust political institutions being more likely to avoid traditional news outlets and turn to social media, thereby reinforcing their distrust. To reduce this bias, linear regression models containing endogenous regressors are generally identified using outside information coming from external instruments. However, in most of the cases, these instruments are not easy to be found and the assumption of exogeneity is not encountered, especially when the analysis deal with individual behaviors as it is the case of this paper. In this sense, the literature on the role of internet on social capital has mainly considered as instruments the presence of the broadband and the quality of connection at home (Falck *et al.* (2014); Geraci *et al.* (2022) among others). Speaking broadly, they refer to two aspects of the internet infrastructure: (i) the speed of a domestic connection is inversely related to the distance from the internet node serving the area and (ii) that the Internet infrastructure was constructed by exploiting the preexisting telephone network, so that the setup costs were reduced. The distance from the node and the setup costs are therefore considered exogenous sources of variation, useful for proper identification since they are strongly correlated with Internet use and orthogonal to social capital.[12] However, for our purpose we believe that, especially for the years considered in our analysis, such instrument may not respect the exogeneity assumption and the effect on our dependent variable may not be indirect. In fact, the choice of having or not the broadband in the house may depend on both family choices (hence hiding some personality traits that could influence the self-reported trust toward politics per sè) or on the impossibility of having such connections at home (due to the lack of the necessary infrastructure in the living area), something that could ultimately affect political trust in a direct way.

For this reason, we here opt for the Lewbel's method (Lewbel, 2012), a well-established technique

[11]More formally, these problems could both determine our main independent variable to be correlated with unobserved factors and our error term to hide heteroscedasticity, finally generating biased and unreliable estimates and hindering identification.

[12]These are only two of the instruments commonly used in the literature. Other studies have also considered the role of rainfall or other weather-related phenomena on the daily use of the Internet, an aspect we do not examine in detail here.

able to reduce the bias by exploiting the heteroskedasticity of the error term without external instruments (or for testing their validity).[13]

This is a data-driven method that consists in using the heteroskedasticity of the error term to build synthetic internal instruments, correlated with the main independent variable and being orthogonal to the model by construction. For a more detailed explanation of the methodology behind the approach, we refer to the original paper by (Lewbel, 2012), the extension with binary endogenous treatment (Lewbel, 2018) and the implementation of this estimator in Stata (deployed with the command "ivreg2h"), by Baum *et al.* (2012).

To our purpose, we here resume the main steps that allow us to clarify how the method works, drawing inspiration from Baum & Lewbel (2019). First, we assume that our model is in the following form:

$$Y_1 = X'\beta + Y_2\gamma + \varepsilon_1$$

$$Y_2 = X'\alpha + \varepsilon_2$$

Where Y_1 is our dependent variable (political trust), Y_2 is our independent binary variable (a dummy representing the information means), and that the error terms ε_1 and ε_2 may be correlated.[14] The standard IV approach requires identifying an element of the X vector that appears in the Y_2 equation but not in the Y_1 equation, thereby serving as an external instrument to isolate the variation in X that is uncorrelated with the error term.

When such an instrument is not available, and the error term ε_2 is heteroskedastic (i.e., an underlying factor, such as a personality trait, affects Y_2 in a heterogeneous way), it is possible to construct an estimator that exploits the information contained in the error term of the second equation. To implement this strategy, we follow the two-step procedure described below:

1. In the first stage (the "auxiliary equation"), we estimate $\hat{\alpha}$ by Ordinary Least Squares, regressing Y_2 on the selected subset of covariates and obtaining the estimated residuals $\hat{\varepsilon}_2 = Y_2 - X'\hat{\alpha}$.[15]

2. In the second stage, we estimate β and γ via Two-Stage Least Squares (2SLS), regressing Y_1 on X and Y_2, and using as instruments X together with $(Z - \bar{Z})\hat{\varepsilon}_2$, where Z denotes some or all of the elements of X, and $\bar{Z}$ is their sample mean.

In words, the internal instrument constructed through this strategy corresponds to the mean-centered exogenous covariates of the model, multiplied by the estimated residuals from the first stage (i.e., $(Z - \bar{Z})\hat{\varepsilon}_2$). These instruments are valid because, by construction, the regressors are uncorrelated with the product of heteroskedastic errors, thereby satisfying the exogeneity requirement. Furthermore, the greater the degree of heteroskedasticity in the error term, the stronger the correlation between the generated instruments and the endogenous regressors, thus ensuring the relevance condition at the first stage. We apply this method to our research questions, finding the following results shown in table 1.10.

[13] It should be noted, however, that while Lewbel's method helps addressing omitted variable bias, it does not control for reverse causality, which therefore remains a possible source of endogeneity in our model.

[14] As Lewbel (2012) notes, error correlations due to unobserved common factors, such as ability or individual traits, are a common feature of many models.

[15] As Lewbel (2018) notes, the first stage can also take the form of a non-linear specification, such as Probit or Logit, which makes the method applicable even when the endogenous regressor is binary.

Table 1.10: *Endogeneity Issues: Results with Lewbel's Method*

	(1)	(2)	(3)
	IV Regression	IV Regression	IV Regression
VARIABLES	PCA of Political Trust	PCA of Political Trust	PCA of Political Trust
Internet Use	-0.0826***		
	(0.0149)		
Social Networks		-0.130***	
		(0.0123)	
Online Newspapers			0.0221*
			(0.0132)
Gender	-0.0147**	-0.0115*	-0.00777
	(0.00679)	(0.00671)	(0.00677)
Age	0.0477***	0.0415***	0.0504***
	(0.00434)	(0.00440)	(0.00431)
Education Level	0.0635***	0.0575***	0.0493***
	(0.00550)	(0.00513)	(0.00546)
Occupation	-0.117***	-0.119***	-0.117***
	(0.00399)	(0.00399)	(0.00399)
Family Structure	-0.0191***	-0.0189***	-0.0190***
	(0.00379)	(0.00379)	(0.00379)
Health Status	0.113***	0.112***	0.113***
	(0.00623)	(0.00623)	(0.00623)
Economic Satisfaction	0.430***	0.428***	0.430***
	(0.00473)	(0.00474)	(0.00474)
Crime Perception	-0.162***	-0.162***	-0.162***
	(0.00398)	(0.00398)	(0.00398)
Internet Frequency	-0.148***	-0.154***	-0.183***
	(0.00998)	(0.00869)	(0.00915)
Region FE	-0.0145***	-0.0142***	-0.0143***
	(0.000580)	(0.000580)	(0.000581)
Years FE	0.112***	0.112***	0.110***
	(0.00136)	(0.00136)	(0.00135)
Observations	234,820	234,820	234,820
R-squared	0.098	0.099	0.098

Note: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The omitted (reference) categories are: Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022)

When using the Principal Component Analysis of political trust as the dependent variable, and applying Lewbel's heteroskedasticity-based instruments, we continue to find a negative and statistically significant coefficient for Internet use, particularly when political information is obtained through social networks. This confirms that, conditional on our set of covariates, online information acquired via social networks has a detrimental effect on trust in government institutions. By contrast, the coefficient for online newspapers is positive, although both its magnitude and significance are now comparatively smaller. Overall, these findings are consistent with a negative association between social media use and political trust, while suggesting that, once accounting for potential omitted variable bias, a causal interpretation of the results is plausible. Nevertheless, caution is warranted: the persistence of potential reverse causality prevents us from fully ruling out concerns regarding the direction of the causal relationship.

1.5 Conclusion

The events that have characterized the last two decades of Europe, from the sovereign debt crisis to the parallel and disruptive digital revolution, leave us clear evidence: political trust is the key to the proper exercise of democracy and preserving it means defending the well-being of the community.

As mentioned in this paper, a lack of trust is potentially harmful and extremely dangerous from a political and social point of view, since the collapse of trust in political institutions can increase barriers to the implementation of policies and consequently hinder economic growth and the social progress of the country (Zak & Knack, 2001).

Moreover, political distrust may also hamper resilience in times of national or international shocks, when citizens are uncertain about the future and both strong public bodies and confidence toward the government's success in tackling the issues are the necessary tools to implement the proper solutions. In this scenario, the disrupting digital revolution and the newest form of online communication add further warnings, especially when considering that most of the potential solution to restore institutional trust revolves around more transparency in communication from the government bodies.

With respect to that, online platforms have now completely transformed the "rules of the game", being individuals able to consult instantly an infinite plurality of information without any kind of specific filters, potentially augmenting political misperception and increasing polarization. With this process being particularly present in social networks, in this paper we explored the link between news consumed online on these platforms (Facebook, Twitter and so on) and political distrust, finding a strong negative effect.

Hence, the results of our estimates open numerous interpretations. To our purpose, we here invoke (i) the need for more regulation in the online information sector, (ii) the levelling of economic inequality, inequality of opportunity and economic insecurity, and (iii) the restoring of government trust on a long-run basis.

The first implication is a direct consequence of the main results of our analysis. Misinformation and disinformation are among the main threats in the modern digital world, and the rapid diffusion of Artificial Intelligence across all working environments adds further reasons for public

intervention (OECD, 2024a).
In light of our findings, we believe that more concrete policy actions should be taken. First, in the domain of digital regulation, governments and supranational institutions could enforce transparency obligations on online platforms, promote independent fact-checking initiatives, and strengthen digital literacy programs to help citizens critically assess online content. These recommendations are aligned with the OECD policy framework, which stresses the need to enhance the transparency, accountability, and plurality of information sources — including both traditional media and online platforms — and to adopt a systemic approach that is co-ordinated, evidence-based, and regularly evaluated to support information integrity (OECD, 2024b).

Second, institutions should complement these interventions with clearer communication strategies and stronger accountability mechanisms, ensuring that citizens can engage with public services and understand policy decisions based on evidence — a key driver of trust in public institutions (OECD., 2022).

Finally, fostering civic and media education from early stages of the schooling system, and encouraging partnerships between governments, civil society, and digital platforms, represent additional steps to build societal resilience against disinformation, as such resilience requires long-term and systemic efforts to empower individuals through media, digital, and civic literacy (Hill, 2022).

Simultaneously, we stress the need for a levelling of the rising socio-economic inequality. Even though this chapter did not directly address these issues, the literature seem still skarn when thinking of how economic disparities may hinder the health of Democracy, reason why we call for further research. Finally, we leave a comment on the long-run detrimental effects of political distrust. With the near-future political Agenda also dealing, among others, with climate change, ageing of the population and labor market revolution, confidence for political bodies is a crucial step to guarantee the efficiency of the interventions and the coordination of collective actions.

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1.6 Appendix

Table 1.11: *Summary Table of the Main Variables*

Dependent Variable	**Description**
Trust toward national government	Using a score of 0 to 10 indicate how much you trust the following institutions: Italian parliament
Trust toward political parties	Using a score of 0 to 10 indicate how much you trust the following institutions: Political parties
Trust toward regional government	Using a score of 0 to 10 indicate how much you trust the following institutions: Regional government
Trust toward municipal government	Using a score of 0 to 10 indicate how much you trust the following institutions: municipal government
PCA of Political trust	Principal Component Analysis of political trust
Independent and Control Variables	**Description**
Use of internet to get political information	Do you get informed about political facts through the Internet?
Use of social networks to get political information	How do you get information on the internet about political facts? Social networks
Use of online newspapers to get political information	How do you get information on the internet about political facts: reading or downloading newspapers or online magazines
Mean of information	How do you get informed about political facts? 1) Offline traditional means (Television, radio, newspapers). 2) Online traditional means. 3) I am not informed about politics at all
Categories of information	How do you get informed about political facts? 1) "Offline" 2) "Not at all" 3) "Online newspapers" 4) "Social networks" 5) "Both means"
Gender	Male/Female: 1: Male, 2: Female
Economic satisfaction	Self-reported economic satisfaction: 1) Poor, 2) Not very, 3) Enough, 4) Good
Family size	Type of family: 1) No family, 2) Couple with children, 3) Couple W/o children, 4) Single parent (male), 5) Single parent (female)
Education level	Qualification: 1) No diploma 2) High school 3) Bachelor/Post degree
Frequency of internet use	How much do you usually use the internet during the year: 1: Less than daily, 2: Daily use
Age category	Age of the interviewed: 1) 14-34, 2) 25-44, 3) 45-64, 4) Over 65
Health status	Self-reported health condition: 1) Bad, 2) No good/bad, 3) Good
Labour market status	Professional status: 1) Inactive, 2) Looking for, 3) Employed
Crime perceived	How much crime do you perceive in the area where you live? 1) High, 2) Enough, 3) Little, 4) No perception
Region	Geographic distribution: residence of the interviewee
Year of the survey	Survey wave: Min: 2014, Max: 2022

Note: Summary and description of the variables under analysis. Source: Author's elaboration from ISTAT (2014–2022).

1.11.b: Descriptive Statistics

	Mean	Std. Dev.	Min	Max	Obs
Dependent Variables					
Trust toward national government	3.965	2.653	0	10	335,466
Trust toward political parties	2.807	2.490	0	10	335,466
Trust toward regional government	4.035	2.651	0	10	335,466
Trust toward municipal government	4.766	2.749	0	10	335,466
PCA of Political trust	2.929	1.734	0	7.585	335,466
Fakenews (dummy)	0.479	0.500	0	1	27,139
Main Independent Variables					
Use of internet	0.364	0.481	0	1	246,826
Use of social networks	0.184	0.388	0	1	246,826
Use of online newspapers	0.274	0.446	0	1	246,826

	Categories (%)					
	1	2	3	4	5	Obs
Independent Variables						
Mean of information	26.8	46.8	26.4	-	-	335,466
Categories of information	46.8	26.4	13.3	6.6	6.9	335,466
Control Variables						
Gender	47.6	52.4	-	-	-	335,466
Economic satisfaction	12.1	33.4	50.4	4.1	-	333,546
Family size	19.5	47.4	22.4	10.7	-	335,466
Education level	48.8	36.6	14.6	-	-	332,650
Frequency of internet use	49.2	50.8	-	-	-	335,466
Age category	11.8	25.5	34.4	28.3	-	335,466
Health status	6.7	28.5	64.8	-	-	335,466
Labour market status	48.7	10.1	41.2	-	-	333,284
Crime perceived	29.5	43.3	21.0	6.2	-	322,250

Note: Descriptive statistics of the variables under analysis. For categorical variables the table reports the distribution of individuals in % across categories. Source: Author's elaboration from ISTAT (2014–2022).

Table 1.12: *Internet use and political trust, 2014–2022 — Ordered Probit estimates*

VARIABLES	(1) O.Probit National gov.	(2) O.Probit National gov.	(3) O.Probit National gov.	(4) O.Probit National gov.
Use of internet	-0.0560***			
	(0.00527)			
Social networks		-0.126***		-0.170***
		(0.00593)		(0.00831)
Online newspapers			0.0203***	0.0118*
			(0.00535)	(0.00628)
Both means				-0.0746***
				(0.00793)
Controls	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	235,888	235,888	235,888	235,888

Note: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Cut-points from ordered probit not reported. All regressions include a constant term as well as region and year fixed effects, though their coefficients are not reported in the table. The omitted (reference) categories are: Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022).

Table 1.13: *Trust in Political Parties, Regional and Municipal Government*

	Political Parties				Regional Government				Municipal Government			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
VARIABLES	Political Parties				Regional Government				Municipal Government			
Use of Internet	-0.0253**				-0.126***				-0.0615***			
	(0.0120)				(0.0126)				(0.0131)			
Social Networks		-0.119***		-0.187***		-0.234***		-0.319***		-0.103***		-0.186***
		(0.0134)		(0.0185)		(0.0142)		(0.0197)		(0.0149)		(0.0206)
Online Newspapers			0.0734***	0.130***			0.0116	0.126***			0.0245*	0.120***
			(0.0123)	(0.0138)			(0.0129)	(0.0145)			(0.0133)	(0.0149)
Both Means				-0.0134				-0.158***				-0.0303
				(0.0183)				(0.0192)				(0.0201)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	235,540	235,540	235,540	235,540	235,674	235,674	235,674	235,674	235,693	235,693	235,693	235,693
R-squared	0.073	0.073	0.073	0.074	0.120	0.121	0.120	0.121	0.101	0.101	0.101	0.101

Note: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include a constant term as well as region and year fixed effects, though their coefficients are not reported in the table. The omitted (reference) categories are: Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022).

Table 1.14: *Heterogeneity by Territorial Divide: North-Centre vs. South*

	Political Trust (PCA)			Trust in National Government		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
Use of Internet	-0.0543***			-0.125***		
	(0.00943)			(0.0146)		
Internet × South	-0.0349**			-0.0543**		
	(0.0145)			(0.0226)		
Social Networks		-0.154***			-0.324***	
		(0.0110)			(0.0171)	
Social Networks × South		0.0242			0.0436	
		(0.0176)			(0.0275)	
Online Newspapers			0.0494***			0.0739***
			(0.00956)			(0.0149)
Online Newspapers × South			-0.0578***			-0.0902***
			(0.0159)			(0.0247)
South	-0.288***	-0.302***	-0.289***	0.248***	0.230***	0.258***
	(0.0216)	(0.0211)	(0.0213)	(0.0136)	(0.0122)	(0.0128)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Regional FE	YES	YES	YES	YES	YES	YES
Observations	234,820	234,820	234,820	235,888	235,888	235,888
R-squared	0.114	0.114	0.113	0.095	0.097	0.095

Note: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include a constant term as well as region and year fixed effects, though their coefficients are not reported in the table. The omitted (reference) categories are: Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022).

Table 1.15: *Age Heterogeneity – Trust in Political Institutions (PCA) and National Government*

VARIABLES	(1) OLS Pol. Trust (PCA)	(2) OLS Pol. Trust (PCA)	(3) OLS Pol. Trust (PCA)	(4) OLS Nat. Gov. Trust	(5) OLS Nat. Gov. Trust	(6) OLS Nat. Gov. Trust
Use of Internet	-0.0829***			-0.197***		
	(0.0215)			(0.0329)		
Internet × Age 15–24	-0.0497**			-0.0709*		
	(0.0251)			(0.0385)		
Internet × Age 45–64	0.0767***			0.176***		
	(0.0243)			(0.0373)		
Internet × Age 65+	0.0176			0.111**		
	(0.0281)			(0.0433)		
Social Networks		-0.118***			-0.292***	
		(0.0220)			(0.0338)	
Social Networks × Age 15–24		-0.0606**			-0.0833**	
		(0.0261)			(0.0402)	
Social Networks × Age 45–64		0.00843			0.0528	
		(0.0264)			(0.0409)	
Social Networks × Age 65+		-0.0736**			-0.00731	
		(0.0366)			(0.0575)	
Online Newspapers			0.0224			0.00421
			(0.0226)			(0.0348)
Online Newspapers × Age 15–24			-0.0367			-0.0395
			(0.0261)			(0.0403)
Online Newspapers × Age 45–64			0.0574**			0.143***
			(0.0255)			(0.0394)
Online Newspapers × Age 65+			-0.00912			0.0474
			(0.0297)			(0.0460)
Age 15–24	-0.150***	-0.166***	-0.163***	-0.240***	-0.273***	-0.261***
	(0.0193)	(0.0170)	(0.0170)	(0.0294)	(0.0260)	(0.0258)
Age 45–64	-0.0874***	-0.0702***	-0.0716***	-0.0180	0.0133	0.0178
	(0.0184)	(0.0163)	(0.0163)	(0.0279)	(0.0249)	(0.0248)
Age 65+	0.0453**	0.0516***	0.0637***	0.171***	0.184***	0.216***
	(0.0196)	(0.0177)	(0.0177)	(0.0299)	(0.0271)	(0.0271)
Controls	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	234,820	234,820	234,820	235,888	235,888	235,888
R-squared	0.114	0.114	0.113	0.102	0.103	0.102

Estimated coefficients on political trust (PCA and national government), including interactions with age categories. Columns (1)–(3) show effects on PCA of trust; columns (4)–(6) on national government trust. Reference group: Age 25–44. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include the full set of controls, regional fixed effects, and year fixed effects (2014–2022). Source: author's elaboration from ISTAT (2014-2022).

Table 1.16: *Heterogeneity by Frequency of Internet Use (Interactions)*

	Political Trust (PCA)			National Government Trust		
	Internet Use	Social Networks	Online Newspapers	Internet Use	Social Networks	Online Newspapers
Internet Use	-0.0585***			-0.129***		
	(0.0170)			(0.0263)		
Frequency of Use	-0.145***	-0.150***	-0.177***	-0.204***	-0.208***	-0.269***
	(0.0100)	(0.00891)	(0.00940)	(0.0155)	(0.0138)	(0.0145)
Internet Use × Freq.	-0.00924			-0.00741		
	(0.0191)			(0.0295)		
Social Networks		-0.199***			-0.403***	
		(0.0258)			(0.0398)	
Social Networks × Freq.		0.0612**			0.110***	
		(0.0273)			(0.0423)	
Online Newspapers			0.0401**			0.0444
			(0.0192)			(0.0296)
Online Newspapers × Freq.			-0.00997			0.0119
			(0.0210)			(0.0324)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Observations	234,820	234,820	234,820	235,888	235,888	235,888
R-squared	0.113	0.114	0.113	0.102	0.103	0.102

Estimated coefficients on political trust outcomes (PCA of Political Trust and National Government Trust), including interactions with frequency of internet use. Columns (1)–(3) report the results on the PCA index, while columns (4)–(6) report results on national government trust. Note: Robust standard errors are reported in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include a constant term as well as region and year fixed effects, though their coefficients are not reported in the table. The omitted (reference) categories are: Male (Gender), Age: 25–44 (Age), Education: High school diploma (Education), Looking for a job (Labor market status), Couple with children (Family size), Health: Bad (Health), No satisfaction (Economic sat), No perception of crime rate (Crime rate), and Internet freq: Sporadic (Internet freq). Year fixed effects correspond to survey waves conducted between 2014 and 2022. Source: author's elaboration from ISTAT (2014-2022).

Chapter 2

Evaluating population heterogeneities in Social and Political trust with an application to Europe

Matteo Sabatini[1]

Abstract

Following the economic downturns of the past two decades, the erosion of trust in institutions and social cohesion has become a pervasive issue that threatens the stability of democratic systems. This chapter explores the evolution of trust over time, examining how these dynamics are shaped by socio-economic gradients before and after major socioeconomic shocks.

To address this, it proposes an intuitive criterion for assessing and comparing trust dynamics over time, accounting for heterogeneities across different socioeconomic groups. This approach provides a framework for evaluating trust within the broader context of welfare analysis.

The empirical analysis, based on data from the European Social Survey (ESS), investigates trust dynamics before and after the two major economic downturns, highlighting the underlying heterogeneity of these trends across two socio-economic dimensions: income deciles, representing a purely monetary measure, and a classification based on inequality of opportunity(IOP) circumstances. As evidence indicates variation between these two groups, the findings highlight the crucial role of socioeconomic disparities in shaping trust and their broader implications for social stability.

Additionally, the analysis provides complementary evidence by considering subjective well-being, a common proxy for individual utility, and finds similar patterns.

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2.1 Introduction

Since the 2009 Stiglitz-Sen-Fitoussi Commission emphasized the need to complement GDP with broader measures of socioeconomic and environmental perceptions, a growing body of research has examined social and institutional trust as both societal and individual indicators of well-being.

As a prosperous society thrives on collaboration, mutual support, and effective public bodies (Stiglitz, 2009), confidence in both other citizens and institutions is essential for social and economic progress that promotes cooperation and collective actions (Ostrom & Ahn, 2009).

For this reason, the debate on social and institutional trust has thus far remained a central element of the political agenda at both the European and national levels. On the one hand, as emphasized by the OECD (OECD., 2022), trust in institutions is fundamental to democracy: it fosters political participation, ensures compliance with regulations, and enables policy change. Prolonged periods of low public confidence not only undermine governments' capacity to operate effectively but also jeopardize the sustainability of democratic systems (Kaasa & Andriani, 2022; Sønderskov & Dinesen, 2016; OECD., 2022).

On the other hand, social (or generalized) trust has typically been associated with economic growth (Knack & Keefer, 1997), as it represents a dimension of a community's social capital, inherited from historical processes and conducive to fostering transactions and pro-social behaviors (Putnam *et al.*, 1994; Algan *et al.*, 2017). Furthermore, empirical evidence indicates that it contributes to improved health, increased employment opportunities, and various dimensions of community life, including lower crime rates.[2]

Given its importance, its recent decline has raised concerns among policy makers, especially after the 2008 financial crisis and the Covid-19 pandemic, as this downward trend has not been fully reversed. As a consequence, in recent years several policy initiatives have stressed the need to re-assess the determinants and consequences of this downward, calling for research to understand how to rebuild social cohesion and trust in public institutions (OECD., 2022).[3]

In this debate, most of the literature has focused on measuring average levels of trust in society, with particular attention to its various components and dimensions, as well as to the identification of its determinants (Kaasa & Andriani, 2022; Durante *et al.*, 2024).[4] By contrast, only a limited number of studies have examined how trust is distributed across individuals within the population.

Recognizing that trust is closely linked to subjective well-being—often employed as a proxy for individual utility (Clark *et al.*, 2008; Clark, 2018)—as well as to factors such as education and health behaviors (Helliwell *et al.*, 2016, 2020; Durante *et al.*, 2024), its distribution emerges as a key determinant of social welfare. An average increase (or decline) in trust may therefore contribute to improvements in overall well-being through multiple channels.

[2] This network of relationships is commonly referred to as *social capital*, underscoring both its direct and indirect benefits.

[3] For instance, Goal n.16 of the Sustainable Development Goals (SDGs), endorsed in 2015 by all UN member states, seeks to "promote peaceful and inclusive societies for sustainable development, ensure access to justice for all, and build effective, accountable, and inclusive institutions at all levels." This underscores the essential role of trust in our society.

[4] Durante *et al.* (2024), for instance, apply a Principal Component Analysis to measures of trust in different institutions to construct a composite index.

Beyond average effects, however, examining heterogeneities in trust is arguably essential not only to assess how unequally this dimension of well-being is distributed, but also to capture its evolution across socioeconomic groups. When these are endowed with differing resources and (dis)advantages, an analysis of distributional dynamics becomes particularly relevant for determining whether recovery processes are not only inclusive but also socially sustainable—namely, capable of fostering long-term well-being across all groups rather than benefiting only the most privileged.
Evidence on the relationship between trust and the distributional characteristics of a population has primarily focused on parametric estimates of the direct effect of income inequality on trust. In particular, the literature has examined how overall inequality is associated with both institutional (Bobzien, 2023; Palmisano, 2023) and generalized trust (Kanitsar, 2022; Barone & Mocetti, 2016), showing that the effect of inequality varies across different segments of the income distribution. Moreover, power distance—that is, the extent to which a society accepts inequality and hierarchical structures—has been found to negatively affect institutional trust (Kaasa & Andriani, 2022).[5] To the best of our knowledge, however, little is known about the socioeconomic gradient in the evolution of trust, leaving open the critical question: *Has the erosion of trust observed in recent years affected all individuals equally?*

One reason for this lack of evidence is that the existing literature has faced substantial challenges related to measurement issues, both in model specification and in the choice of variables. Moreover, much of the analysis on trust (and well-being, more broadly) relies on a cardinalization procedure, which inherently assumes that the difference between successive categories is uniform. Yet, as noted by Allison & Foster (2004), when variables are measured in surveys using a Likert scale or another ordinal scale with k categories assigned arbitrary values, applying cardinalization is not always appropriate, since such variables do not preserve their mean when the scale changes.

This paper addresses these issues by proposing a non-parametric methodology based on the CDF comparison index, popularized by Cowell & Flachaire (2017, 2018), thereby providing detailed insights into the distribution of trust variations across social groups. Specifically, the method builds on individual trust changes within distinct population segments and employs trust dynamics curves to establish robust rankings of trust evolution.

This methodology offers several advantages. First, it enables the assessment of whether and how trust dynamics vary across different socioeconomic categories in the population, facilitating comparative analyses of trust shifts. By highlighting the variations among distinct subgroups, this framework incorporates the social gradient of trust into the evaluation process. Second, the approach aligns with a broad definition of trust and can be applied to cases where trust indicators are either numerical or purely ordinal. Third, it provides a normative justification for its implementation, advocating for the use of trust dynamics curves alongside additional measurement tools (e.g., cumulative curves) to enhance evaluation when standard trust metrics alone prove insufficient.

We apply this model to assess trust trends across Europe from a pan-European perspec-

[5] In other words, when individuals have greater opportunities to influence public decisions, their confidence in national institutions tends to grow (Guiso *et al.*, 2019, 2024; Ivanov, 2023).

tive. Most of the existing literature on social and political trust has focused on cross-country comparisons, exploiting institutional and cultural differences. In light of the recent discussion by Milanovic (2016), however, this study undertakes one of the first pan-European analyses, focusing on perceived trust in institutions and interpersonal trust as the key variables.

Differences in trust dynamics are examined using two distinct socioeconomic classifications: relative position within the income distribution and socioeconomic background. While the former reflects differences in economic resources and purchasing power, the latter, as discussed in Section 3, is particularly relevant for considerations of equality of opportunity (Fleurbaey & Schokkaert, 2009; Palmisano & Peragine, 2022; Roemer & Trannoy, 2015), given the growing consensus that the influence of family background on individual opportunities should be minimized. The growing gap between citizens and political leaders in their perception of democracy, reflected in low trust in public institutions and higher segregation, underscores the importance of examining how different socio-economic backgrounds shape community perceptions, especially in light of the recent decline in political participation (Stiglitz, 2009) and polarization of beliefs Alesina *et al.* (2020). Thus, exploring how unfairness may segregate individuals' confidence toward institutions and other citizens depending on their socio-economic background not only can be considered interesting per sè, but it is also fundamental in order to design the proper political interventions.

The main findings show that social inequalities have played a key role in shaping trust dynamics in Europe. However, the specific patterns of trust evolution strongly depend on how the population is categorized. When society is divided based on a monetary measure, such as income deciles, trust follows a progressive pattern. In contrast, a classification based on socioeconomic background suggests a regressive trend.

At a theoretical level, this study contributes by introducing a new tool for measuring and comparing trust evolution, which can be applied regardless of whether the variable is ordinal or cardinal and independently of the socioeconomic status partition used. At an empirical level, our research represents the first large-scale European analysis of trust dynamics.

The rest of the paper is structured as follows: Section 2.2 defines the concept of Trust Dynamics Curve (TDC) and Section 2.3 introduces tools for evaluating these dynamics under welfare evaluation. Section 2.4 presents the empirical application, while Section 2.5 provides a complementary analysis using subjective well-being variables, specifically self-reported happiness. Finally, Section 2.6 concludes.

2.2 Measurement Method

Although well-established methods and data sources provide a relatively reliable way to measure the socioeconomic gradient in economic inequalities, evaluating dynamics and disparities in non-monetary aspects—such as social and institutional trust—remains significantly more challenging. Thus, capturing heterogeneities in trust and understanding the underlying socioeconomic gradient requires first addressing the choice between a parametric and a non-parametric approach.

So far, as noted in Section 2.1, the literature has primarily focused on correlations between the variables of interest, namely the Gini coefficient and different forms of trust (institutional and interpersonal). However, correlation (or elasticity) coefficients over two points in time, derived from parametric approaches, are designed to capture linear relationships between variables, which may be inadequate if the goal is to uncover heterogeneity across time and subgroups (Cowell & Flachaire, 2018). Moreover, if the aim is to capture how trust is distributed within a population, relying on average trust can be misleading, since individual observations at different parts of the distribution may reveal distinct patterns.

For these reasons, this work adopts a non-parametric approach, as it treats individual observations more transparently and allows for the visualization of the entire distribution of trust. In addition, non-parametric methods are generally better suited for handling ordinal data, an issue discussed in greater detail below.

For the purposes of this study, dynamics in trust are interpreted as the intensity with which subjective trust improves or declines between two periods across different socio-economic groups (SES), thereby capturing the socio-economic gradient within the population. Hence, to conduct our analysis we need the following three ingredients, in the spirit of Cowell & Flachaire (2018) on mobility:

1. A time frame t, with $t \in \{1, \dots, n^T\}$.
2. A set of $\mathcal{N}_t = \{1, 2, \dots, n_t\}$ individuals observed at time $t \in \{1, \dots, n^T\}$, indexed by i and, partitioned into G groups $g = 1, \dots, G$ reflecting the socio-economic gradient.
3. A measure of trust $\pi_{i,t}$ defined for each individual i at time t and comparable across groups and periods.

With reference to 1, a two-period framework is adopted, which can be broadly interpreted as a before-and-after analysis of a given shock. This assumption is not restrictive, as the framework can be extended to multiple periods, thereby enabling a more comprehensive dynamic assessment.

With respect to 2, the following assumption is required: within each group g, individuals are assumed to share the same socio-economic characteristics, corresponding to any possible definition of Socio-Economic Status (SES) that may structure a society and reflect its socio-economic gradient.

Then, for each of the groups defined, we denote by $q_t^g = \frac{|N_t^g|}{|N_t|}$ the group-specific population share at time t, allowing for variable population size across groups.

It is further assumed that a normative ranking of groups can be established on the basis of their position in the initial distribution of the mean outcome z (e.g., income or consumption expenditure), which serves as a proxy for the average standard of living within each group. Let $\mu_{(g)t}(z)$ denote the average outcome z of group g in the initial period; groups can then be ordered such that $\mu_{(1)t}(z) \leq \mu_{(2)t}(z) \leq \cdots \leq \mu_{(G)t}(z)$. Alternative rankings of SES can, of course, also be incorporated into the model.

Point 3 deserves further attention. As emphasized by Allison & Foster (2004) and Cowell & Flachaire (2017), unlike income or wealth, which can be directly measured and compared across individuals, subjective indexes are harder to quantify, as they are typically measured through ordinal data. For such data, where only the category labels $k = 1, 2, \dots, K$ and the number of individuals n_k in each category are available, values can be ranked but lack a clear numerical scale, and their means are not scale-invariant.

To address this issue, this work adopts the concept of *status* popularized by Cowell & Flachaire (2017), initially applied as a robust measure of health status based on self-assessed health. This approach makes it possible to model trust dynamics for both ordinal and cardinal outcome variables, since distributional orderings derived from CDF comparisons remain robust to scale changes.

The concept of *status* rests on an individual's position within a distribution, a perspective common in studies of income distribution, where it has been used to construct indicators of individual deprivation (distances between positions) and to assess inequality at the societal level.

Formally, if u_i denotes the utility of individual i and F is the distribution function of u for a population of size n, the *status* of each individual, s_i, is uniquely determined by the distribution and corresponds to the individual's relative position within it. This relative position refers to the proportion of individuals who rank at or below a given person in the distribution.

Given that F represents the cumulative distribution function of utility in the population, *status* can be defined as:

$$s_i = F(u_i) = \int_{-\infty}^{u_i} f(u)\, du \tag{2.1}$$

This assumes only that individuals within the same category share the same *status* relative to the population and that the utility concept under analysis is ordinal, applicable to both cardinal and categorical variables. Thus, the proposed model can be applied to assess trust dynamics robustly, regardless of whether the outcome is measured through cardinal or ordinal variables.

Considering two generic periods t and $t+1$, assume the existence of an ordered set of $K > 2$ classes, with each class indexed by $k = 1, 2, \ldots, K$ and associated with a latent level of trust (e.g., confidence in institutions or satisfaction with government policies). Let $k_t(i)$ $(k_{t+1}(i))$ denote the class occupied by individual i at time t $(t+1)$; n_k^t (n_k^{t+1}) the number of individuals in class k at time t $(t+1)$; and N_t (N_{t+1}) the total population size at time t $(t+1)$.

An individual *status* or *achievement* in terms of this measure of social capital can be defined as follows.[6]

$$\pi_t^i = \frac{\sum_{j=1}^{k_t(i)} n_{j,t}}{N_t} \quad \forall\, i = 1, \ldots, N_t; \quad \pi_{t+1}^i = \frac{\sum_{j=1}^{k_{t+1}(i)} n_{j,t+1}}{N_{t+1}} \quad \forall\, i = 1, \ldots, N_{t+1}. \tag{2.3}$$

Building on this definition, and incorporating points 1–3, it is now possible to derive a measure of trust dynamics that accounts for the social gradient. Let the population N_t be divided into n_G subsets, and $|N_t^g|$ the set of individuals belonging to group g at time t, with $g \in \{1, \ldots, n_G\}$ and $t \in \{1, \ldots, n_T\}$.

[6] The procedure described here applies to both categorical and continuous variables. In a more general setting, let $N_t = \{1, 2, \ldots, n_t\}$ denote the set of individuals at time $t \in \{1, \ldots, n_T\}$. For individual i, the declared trust δ_t^i corresponds to its position in the CDF of the population distribution, so that

$$\pi_t^i = \int_{\underline{\delta}}^{\delta_t^i} dF_t(\tilde{\delta}), \tag{2.2}$$

with $F_t(\tilde{\delta})$ denoting the CDF of declared trust at time t. For continuous variables, π_t^i is uniformly distributed on $[0, 1]$.

The *trust achievement* of group g at time t is then defined as:

$$\tau_t^g = \frac{1}{|N_t^g|} \sum_{i \in N_t^g} \pi_t^i \quad ; \quad \tau_{t+1}^g = \frac{1}{|N_{t+1}^g|} \sum_{i \in N_{t+1}^g} \pi_{t+1}^i. \tag{2.4}$$

In words, the *achievement* of individual i at time t $(t+1)$ is given by the fraction of individuals in t $(t+1)$ who belong to the same or to a lower class than the class attained by that individual. The *achievement* of each SES at time t $(t+1)$ corresponds to the average trust status of the individuals belonging to group g at time t $(t+1)$.

2.2.1 Trust dynamics curve

Following the above definition of group-level achievements, we now introduce the Trust Dynamics Curve (TDC), which summarizes how trust evolves across socioeconomic groups over time.

$$\Delta\tau^g = \tau_{t+1}^g - \tau_t^g, \quad \forall\ g = 1, \ldots, G \tag{2.5}$$

TDC is obtained by plotting, for each socio-economic status (SES) group g, the difference between *trust achievement* at time $t+1$ and *trust achievement* at time t, with groups sorted in increasing order according to their average outcome z in the initial period.

The TDC allows assessing trust dynamics at a disaggregated level, incorporating the socio-economic gradient in a consistent way for both cardinal and ordinal utility outcomes. Since achievement is distribution-dependent, τ^g represents a relative measure of change, meaning that dynamics are evaluated based on how much better or worse the utility achievement of each SES group is in the present compared to the past. Graphically, when TDC is plotted against each g, it will be zero in the case of no change.

If individuals belonging to the SES group g at time $t+1$ attain the same achievement as individuals in the same SES at time t (or progress only slightly), while other SES groups progress significantly more, then individuals in group g at $t+1$ will dominate fewer people than those in the same group at t. As a result, the change score of group g will be negative.

Thus, we refer to negative (positive) trust change to indicate relative deterioration (improvement) in trust achievement. Furthermore, if the TDC is increasing (decreasing), the trust dynamic is deemed regressive (progressive) with respect to SES.

Since the population size of each sub-group may be different, this variation may influence the evaluation of a dynamics in a way that is not fully captured by the TDC defined in Equation 2.5. For this reason, recalling $q_t^g = \frac{|N_t^g|}{|N_t|}$, it is useful to define a weighted version of the TDC as follows:

$$\hat{\Delta}\tau^g = q_t^g \cdot \Delta\tau^g, \quad \forall g = 1, \ldots, G. \tag{2.6}$$

Assume that two SES groups, j and h, experience the same trust dynamics as measured by the TDC, so that $\Delta\tau^j = \Delta\tau^h$, but differ in population size, with $q_t^j > q_t^h$. In this case, the weighted change measure associated with group j will be larger than the corresponding weighted change measure for group h.

In our empirical application, we consider two alternative group partitions. One follows the equality of opportunity literature, defining groups based on individuals' childhood circumstances (Ramos & Van de Gaer, 2016), the other is based on a more pure measure of economic well-being, namely income deciles. However, our model is general and can also be implemented using other socioeconomic status (SES) partition, such as self declared SES status or education level. The derived measure serves as a useful graphical tool to illustrate the evolution of trust across different parts of the distribution. However, we further question whether these measures can be incorporated into a normative analysis to assess whether a given trust pattern can be considered sustainable from a normative perspective.

Therefore, before presenting the graphical illustration, we introduce the normative characterization in Section 2.3 below.

2.3 Normative Characterization

The weighted and unweighted TDC, introduced in the previous section through equations (2.5) and (2.6), can provide a detailed and comprehensive perspective on the evolution of trust across socioeconomic groups. However, while they illustrate observed trends, they do not directly yield normative insights.

Institutional trust is positively associated with greater compliance with rules, lower tax evasion, and serves as a fundamental pillar of social cohesion, while low trust can lead to inefficiencies and increased legal compliance costs (Bjørnskov, 2009; Besley, 2020; Knack & Keefer, 1997).

Similarly, higher social cohesion often reflects a dynamic and well-functioning society, contributing to greater socio-economic benefits (see Putnam *et al.* (2001), among many others).

Thus, we can reasonably assume that the social planner is endowed with preferences over the outcome distributions of trust, and that these preferences are such that:

i) A trust dynamic is socially desirable if the change in social welfare associated with a given change in the distribution of trust in the population is positive.

ii) Given two alternative dynamics, one is normatively superior to the other when the welfare change associated with one process is larger than the welfare change associated with the compared process.

iii) These preferences incorporate a greater (lower) sensitivity to the upward (downward) movement of specific subgroups.

While the first two points are the natural consequence of a standard monotonicity property, the third is necessary to account for the specific SES partition. Socioeconomic inequality has long been shown to weaken cohesion and erode institutional trust through several mechanisms: it increases the perceived distance between citizens and political rulers, signals exploitation and government ineffectiveness, and generates negative externalities such as crime and instability, all of which reduce confidence in institutions (Delhey & Kohler, 2007; Turper & Aarts, 2017). As highlighted more recently by Palmisano & Sacchi (2024), these mechanisms imply that declines in trust among lower SES groups are particularly consequential, thus providing a justification for giving greater normative weight to changes in these groups when evaluating trust dynamics.

Since the objective is to measure welfare changes and establish whether some outcomes are preferable to others, an improvement in the position of certain subgroups—while others remain unchanged—should be regarded as a welfare improvement (or deterioration), depending on the subgroup concerned.

Our starting point is then a class of rank-dependent social evaluation functions that are explicitly sensitive to changes in the relative position of individuals with different SES characteristics within the outcome distribution.

To represent these preferences, we adapt the rank-dependent model introduced by Yaari (1987), which provides both theoretical and empirical tractability. This model assumes that social welfare can be expressed as a weighted average of all possible outcomes, where the weights depend on their ranking. Applied to our trust dynamics framework, the social evaluation function for a trust distribution at time t corresponds to the average status achieved across all SES groups in the population, where w^g denotes the weight assigned to group g and the function is defined as follows:

$$W_t = \sum_{g=1}^{n_G} w^g q_t^g \tau_t^g \tag{2.7}$$

The change in social welfare associated with an outcome distribution between two periods of time is then:

$$\Delta W = \sum_{g=1}^{G} w^g q_{t+1}^g \tau_{t+1}^g - \sum_{g=1}^{G} w^g q_t^g \tau_t^g \tag{2.8}$$

or equivalently,

$$\Delta W = \sum_{g=1}^{G} w^g \left(\tau_{t+1}^g \, \Delta q^g + q_t^g \, \Delta\tau^g\right) \tag{2.9}$$

where $\Delta q^g = q_{t+1}^g - q_t^g$ and $\Delta\tau^g = \tau_{t+1}^g - \tau_t^g$.

The social evaluation of any dynamic process of the outcome variable corresponds to the change in the weighted mean of group status, with weights reflecting both subgroup composition and normative importance.

The different preferences over the subgroups, that is the attitudes of a social planner toward the social gradient behind a specific dynamic, are expressed through the weight w, which represents the marginal effect of changes in trust on social welfare for each specific SES group in the population.

Thus, a normative evaluation of our outcome dynamics concept can be obtained as a weighted sum of the individual status changes, where these changes are aggregated across SES groups according to their average standard of living at the start of the observation period, as discussed above.

If the values of w_g were known, we could directly carry out these assessments. However, since this information is unavailable, we have, in principle, to perform a sensitivity analysis over a reasonable range of preferences, which we do by imposing certain restrictions.

Specifically, (i) we redefine dominance in terms of observable factors, meaning that preferences over outcome dynamics are expressed as functions of the observed achievement distributions, and (ii) we make some constraints regarding sub-population composition.

In practice, for (i) we consider the following two classes of social preferences towards outcome distribution dynamics:

$$P = \{W : w^g \geq 0 \ \forall g = 1, \dots, G\}$$

$$P^* = \{W \in P : w^{g-1} \geq w^g \geq 0 \ \forall g = 2, \dots, G\}$$

The first class, P, represents the set of social evaluation functions that incorporate the standard monotonicity property mentioned above. That is, a social planner endorsing such preferences likes increase in trust achievements and dislikes reductions: it attaches non-negative weight to the trust achievement change experienced by each SES in the population.

The second class, P^* , refers to the set of social evaluation functions that enable us to account for the social gradient in the evaluation of a trust dynamics. A social planner endorsing such preferences is more sensitive to the changes in achievement experienced by more disadvantaged SES than to the same amount of change in trust achievement being experienced by less disadvantaged SES: it attaches higher weights to the change in trust achievement experienced by SES with lower standard of living.

For (ii), we assume the population share of our groups remains constant across two periods of time. This leads to two cases: one being more general and arising when the same population (with its relative sub-population share) is observed in both periods, and the other being its special case, occurring when the division consists of equally sized groups, such as in a quantile-based partition of a given distribution. As a consequence, assessing social desirability only requires focusing on the unweighted TDC, as formalized in the following Remarks b of Proposition (2), (3), and (4) below. According to our model, the following Propositions hold:

Proposition 1. *When $q_t^g = q_{t+1}^g$ for all $g = 1, \dots, G$, a trust dynamic is socially desirable for all $W \in P$ if and only if*

$$\Delta\tau^g \geq 0 \quad \forall g \in \{1, \dots, G\}.$$

As a result, a trust dynamic is deemed socially desirable when the TDC coordinates are positive for each group g, as this ensures that every SES group experiences an improvement in trust achievement. Proposition 1 further establishes that the positivity of the unweighted TDC is a sufficient condition for welfare improvements, providing a normative characterization of the TDC, which would otherwise serve only as a graphical tool.

Thus, assessing TDC dominance by comparing observed trust dynamics with a hypothetical no-change scenario (*i.e.*, a TDC where all coordinates are equal to zero) is a sufficient condition for achieving welfare improvements over time.

Arguably, this result is useful not only for evaluating a single curve but also for comparing different trust dynamics and ranking them under welfare evaluation, which is the case formalized in Proposition 2.

For simplicity, assume that we need to compare two trust dynamics, each leading to a different level of social welfare change, denoted as $\Delta W(\pi)$ and $\Delta W(\omega)$, respectively. The former is preferred to the latter if it results in a greater welfare change, i.e., $\Delta W(\pi) \geq \Delta W(\omega)$.

Proposition 2. *Given two trust dynamics generating, respectively, $\Delta W^{(\pi)}$ and $\Delta W^{(\omega)}$, and holding constant the group-specific population sizes, the former is socially preferred to the latter for all $W \in P$ if and only if*

$$\widehat{\Delta}\tau^{g,(\pi)} \geq \widehat{\Delta}\tau^{g,(\omega)} \quad \forall g \in \{1, \ldots, G\}.$$

Proposition 2 establishes the first-order dominance criterion based on weighted TDCs, requiring the verification of one dynamic process's dominance over another for every SES group. It also leads to a special case, formalized in Remark 2b, which applies when the population share of each group remains unchanged over time (i.e., the partition consists of equally sized groups). In this scenario, social desirability is determined by examining the unweighted dominance of TDCs.

Remark 2b. Given two trust dynamics generating, respectively, $\Delta W^{(\pi)}$ and $\Delta W^{(\omega)}$, in the presence of equal population sizes across groups that remain unchanged over time, the former is socially preferred to the latter for all $W \in P$ if and only if

$$\Delta\tau^{g,(\pi)} \geq \Delta\tau^{g,(\omega)} \quad \forall g \in \{1, \ldots, G\}.$$

With our relative concept of trust dynamics, achieving dominance is particularly difficult. In relation to Proposition 1, the zero-sum nature of rank changes implies that the condition cannot be satisfied when comparing the entire population to the benchmark of no change in the average status across SES groups, as dominance can only arise in the trivial case where $\Delta\tau^g = 0$ for all groups, leaving social welfare unchanged.[7]

Moreover, even if dominance remains theoretically possible in the other contexts, identifying dominance empirically in Proposition 2 (and Remark 2b), still remain difficult, as first-order dominance relies on social evaluation functions that impose only weak restrictions. While these

[7]For instance, if a single individual increases his declared trust from δ_1 to δ_2 between t and $t+1$, those with trust levels below δ_1 or above δ_2 remain unaffected, while those between δ_1 and δ_2 experience a reduction in their relative rank π^i_{t+1}. This raises the average trust of the individual's group but necessarily reduces it for at least one other group.

restrictions are widely accepted, they require that change in the distributions to pass highly strong tests.

Nonetheless, if two TDCs intersect, it is still possible to explore higher-order dominance results. These represent minimal refinements in the set of admissible preferences, allowing for an unambiguous assessment of trust dynamics, as introduced in the following propositions.

Proposition 3. *When $q_t^g = q_{t+1}^g$ for all $g = 1, \ldots, G$, a trust dynamic is socially desirable for all $W \in P^*$ if and only if*

$$\sum_{g=1}^{G} \widehat{\Delta}\tau^g \geq 0.$$

Compared to Proposition 1, Proposition 3 relaxes the requirement of non-negative changes for each group by allowing for compensation across groups. In this case, some groups may experience a decline in average trust, but as long as these losses are offset by larger gains in other groups, the overall variation remains non-negative and the trust dynamics is considered socially desirable. This reflects a weaker but more realistic dominance condition[8].

As in Proposition 2, when the population size remains constant across groups and does not change over time, determining the social desirability of a trust dynamic is sufficient by verifying the non-negativity of the coordinates of the cumulated unweighted TDC.

Remark 3b. When population sizes are equal across groups and remain constant over time, a trust dynamic is socially desirable for all $W \in P^*$ if and only if

$$\sum_{g=1}^{G} \Delta\tau^g \geq 0.$$

Consequently, when a social planner is concerned with the comparison between two alternative trust dynamics and their respective social gradient, the normative superiority of one trust dynamic over another can be established by verifying the cumulated versions of the conditions characterized in Proposition 2. In detail:

Proposition 4. *When group-specific population sizes remain constant over time, given two trust dynamics generating, respectively, $\Delta W^{(\pi)}$ and $\Delta W^{(\omega)}$, the former is socially preferred to*

[8]This logic corresponds to the standard compensation principle in welfare economics: social improvement can be acknowledged even when not all subgroups benefit, provided that the aggregate outcome satisfies the dominance criterion. In this sense, Proposition 3 is also close to the Pigou–Dalton transfer principle, whereby redistributive shifts are admissible as long as they do not reduce aggregate welfare.

the latter for all $W \in P^*$ if and only if

$$\sum_{g=1}^{j} \widehat{\Delta}\tau^{g,(\pi)} \geq \sum_{g=1}^{j} \widehat{\Delta}\tau^{g,(\omega)} \quad \forall j = 1, \ldots, G.$$

Remark 4b. When population sizes are equal across groups and remain constant over time, given two trust dynamics generating, respectively, $\Delta W^{(\pi)}$ and $\Delta W^{(\omega)}$, the former is socially preferred to the latter for all $W \in P^*$ if and only if

$$\sum_{g=1}^{j} \Delta\tau^{g,(\pi)} \geq \sum_{g=1}^{j} \Delta\tau^{g,(\omega)} \quad \forall j = 1, \ldots, G.$$

Building on the definition of the Trust Dynamic Curve (TDC) and the normative proposition outlined above, we can now analyze trust dynamics and provide a corresponding normative evaluation of the curves related to social and political trust in Europe, with SES defined by Types and an income decile partition.

2.4 Data and Empirical illustration

We move on to the graphical representation of the curves derived above, opting for a Pan-European perspective of trust toward institutions. To reflect the Pan-European perspective and to account (partly) for heterogeneities between national government, we here focus on trust toward European Parliament, hence reflecting how individual perceived this political body depending on their Socio-economic position in the european society.

To our knowledge, this is one of the first works focusing on European institutions, as most of the works related to the determinant of political trust have mainly focused on cross-country comparisons of trust toward the respective national governments.

To do so, we extract data from the European Social Survey (ESS)[9]. The European Social Survey (ESS) is an academically driven, multinational survey that has been carried out across Europe since its launch in 2002 and conducted biennially ever since. It involves face-to-face interviews with selected cross-sectional samples, with a sampling process employing a strict random probability methods at each stage, in order to ensure representation of the entire residential population aged 15 and above. By the conclusion of the eleventh round in 2022/23, more than 475,000 interviews had been conducted across the European continent since 2002. The ESS aim is to create a reliable dataset for scholars, researchers, and policy makers to analyze and compare social attitudes, beliefs, and behaviors across European countries. For the purposes of this study, the survey provides specific questions central to the analysis, including items on social and political trust, as well as on subjective well-being and overall life satisfaction. The main variable of interest—trust in the European Parliament—is measured through the question: *"Using this card, please tell me how much you personally trust each of the following institutions,"* with the European Parliament listed first.

Similarly, social trust is evaluated using the Rosenberg question: *"Generally speaking, would you say that most people can be trusted, or that you cannot be too careful in dealing with people?"*

Both questions are measured on a scale from 0 to 10, where 0 indicates no trust at all in an institution (or others), and 10 signifies complete trust.

Subjective well-being (life satisfaction) is then assessed with the question: *"All things considered, how happy (satisfied) are you with your life as a whole?"* Responses are given on a scale from 1 (extremely unhappy) to 10 (extremely happy).

Since the 2002/03 survey, a total of 38 countries have participated in at least one round of the survey, while 10 European nations have consistently taken part in all round. We recognize this could generate a bias in our result coming for the over-representation of some countries. However, as shown in Table 2.3 in the appendix, the distribution of responses across countries and survey years is well balanced, as ensuring representativeness is one of the goals of the ESS. This means that no country in our sample dominates the others, as no single country exceeds 10% of the total representation.

Moreover, to further minimize potential biases, all variables in our analysis are consistently

[9]The proposition derived above would likely suggest using a panel dataset to better control for changes in group sizes over time (survey waves). However, we choose this dataset for illustrative purposes in the context of trust. Moreover, as shown in the appendix, group sizes do not change significantly over time due to the consistent sampling process used by the ESS.

weighted using the sample weights provided by the ESS[10].

Finally, to focus exclusively on European countries and their respective trust in the European Parliament, we exclude countries that do not belong to the European Union. The final sample is therefore a pan-European aggregate of the following nations: Austria (AT), Belgium (BE), Bulgaria (BG), Cyprus (CY), Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), Greece (GR), Croatia (HR), Hungary (HU), Ireland (IE), Italy (IT), Lithuania (LT), Latvia (LV), Netherlands (NL), Poland (PL), Portugal (PT), Romania (RO), Sweden (SE), Slovenia (SI), and Slovakia (SK).

The model described in Section 2 requires at least two time periods to assess a Trust Dynamic curve that incorporates the socio-economic gradient.

For the purpose of this study, we select four rounds of the ESS, specifically those collected in 2008, 2012, 2018, and 2022. This arbitrary choice is based on two main reasons. First, we aim to cover a long time span, as the dataset is not a panel, and differences between two rounds may be difficult to interpret. Secondly, during periods of national or international shocks, a lack of social cohesion and political distrust might hinder resilience, as confidence in the government's ability to address crises and high social capital are essential factors for stability. Thus, we choose these specific waves to evaluate whether trust in the European Parliament and trust in others has changed following the two most significant crises of the past two decades, namely the 2010 sovereign debt crisis and the COVID-19 pandemic.

This analysis could provide further insight into how these two fundamentally different crises—one economic and one health-related—have affected the population differently, depending on their specific socio-economic position within European society.

To capture the socioeconomic gradient of groups G, we consider two alternative partitions:

- a purely monetary indicator of economic well-being, namely *income deciles*;
- a classification based on *socio-economic background*.

For the first partition, individuals are divided into ten groups according to the deciles of their national income distribution. In the ESS, income deciles are constructed from national distributions of total net household income (after taxes and compulsory deductions), using official sources such as EU-SILC or national registers.[11]

The first partition thus follows a standard approach that groups the population by position in the income distribution, whereas the second is rooted in the equality of opportunity literature, defining groups on the basis of individuals' childhood circumstances (Ramos & Van de Gaer, 2016; Roemer & Trannoy, 2015). This dual approach allows the results to be interpreted both in terms of fairness in outcomes and in terms of "leveling the playing field" considerations.

We then divide the sample into *types*, which represent a vector of characteristics that are considered beyond individual control, that are rewarded differently, and that should be compensated for in a fair society.

[10] See ESS for a detailed discussion on the appropriate sample weights for a pan-European analysis.

[11] Respondents are presented with a showcard listing income ranges corresponding to each national decile and are asked to select the category that best matches their household income. Thus, individuals do not compute their own decile but self-place into one of the predefined categories, which are country-specific rather than European.

As circumstances, we choose gender, and parental education level, from which we take the highest value of parental education reached by the two parents. The value of parental education is provided from ESS and follows the standard ES - ISCED notation. We compress the variable into 4 category, which we assign value equal to 1 if the highest level of parental education is "less than lower secondary", 2 if "lower secondary school", 3 if "high school", 4 if the highest level reached is "Bachelor degree or more"[12].

Types are then constructed based on the interaction of the selected circumstances, a procedure that results in a total of (well-balanced) 8 types[13], as described in Table 2.1. Table 2.2 instead gives an overview of the descriptive statistics of the variable used for our analysis. For further descriptives, we refer to the appendix, where we show the distribution of responses by each category of trust by each of the subgroups selected for the years considered (tables 2.4, and 2.5) and for further details regarding the respective subgroup composition and their variability (tables 2.6 and 2.7).

Table 2.1: *Distribution and description of types*

Type N°	**Description**	**Frequency**	**Percent**
1	Females + primary school P.E.	12,318	13.45
2	Females + secondary school P.E.	8,865	9.68
3	Males + primary school P.E.	11,033	12.04
4	Males + Secondary school P.E.	7,652	8.35
5	Females + High-school P.E.	19,505	21.29
6	Males + High-school P.E.	17,999	19.65
7	Females + Bachelor or more P.E.	7,258	7.92
8	Males + Bachelor or more P.E.	6,971	7.61
Total		91,601	100.00

Note: Types are ordered by the average decile of income of the individual in the type. Source: our elaboration from European Social Survey

[12]The original variable is in 8 categories, which are:The seven levels of ES-ISCED are: (1) ES-ISCED I: less than lower secondary, (2) ES-ISCED II: lower secondary, (3) ES-ISCED IIIb: lower tier upper secondary, (4) ES-ISCED IIIa: upper tier upper secondary, (5) ES-ISCED IV: advanced vocational, sub-degree, (6) ES-ISCED V1: lower tertiary education, BA level, (7) ES-ISCED V2: higher tertiary education, MA level or above

[13]The literature on equality of opportunity has been extensive, and many different approaches to defining types have been used (see for example Brunori *et al.* (2023) for a recent discussion on the various methods for defining types). For this analysis, we refer to Table 2.7 in the Appendix for the distribution of types in our sample.

Table 2.2: *Descriptive Statistics*

VARIABLES	Obs	Median	Min	Max	
Most people can be trusted	91,601	5	0	10	
How satisfied with life	91,601	8	0	10	
Trust in the European Parliament	91,601	5	0	10	
How happy are you	91,601	8	0	10	
Father's Education	91,601	3	1	4	
Mother's Education	91,601	2	1	4	
Highest Education	91,601	3	1	4	
Father's Occupation	91,601	1	0	1	
Mother's Occupation	91,601	1	0	1	
Highest Occupation	91,601	1	0	1	
Gender	91,601	0	0	1	
Types	91,601	5	1	8	
Observations	91,601	-	-	-	-

Note: Descriptive of the main variables.Source: author's elaboration from European Social Survey (2008-2022). The variables are extracted from ESS round relative to 2008, 2012, 2018,2022.

2.4.1 Political Trust in Europe

Before presenting the results of our normative analysis, we first outline some descriptive patterns regarding the weighted TDC for the rounds of our study and the two specific subgroups considered for both institutional and social trust.[14] It is important to emphasize that the observed differences are generally subtle and that our graphical approach does not allow us to assess their statistical significance or provide confidence intervals.[15]

Two main aspects emerge from the graphs. First, the distinction between income deciles and fairness appears relevant when analyzing social and institutional trust, as evidenced in most of the figures below. As shown in Figure 2.1, the TDC follows opposite patterns depending on the subgroup partition. Specifically, for the 2012–2008 period (i.e., changes measured from 2012 back to 2008), the TDC based on income deciles (left panels) appears progressive, increasing for lower deciles, whereas the type-based partition (right panels) exhibits a regressive pattern.

In contrast, the opposite trend is observed in the most recent period (2023–2018), where the TDC based on income deciles displays a regressive pattern, while the type-related TDC shows a slightly progressive trend.

Second, the graphs suggest distinct effects associated with the two socioeconomic shocks under analysis. The method implemented indicates a stronger response from the middle class (in terms of deciles) following the 2010 sovereign debt crisis, whereas a marked decline is visible after the COVID-19 crisis. This could arguably be attributed not only to the pandemic itself but also to the subsequent economic downturn.

[14]For these graphs, all TDCs are weighted to allow for better comparison in terms of the magnitude of changes.
[15]Hence, the graphs should be interpreted as indicative patterns rather than robust statistical evidence.

Relatively stable patterns are observed during the intermediate period (2018–2012, middle panels). The curve for political trust appears slightly regressive when considering income deciles, while it remains relatively stable for the type partition. The only exception is a decline for the type numer 5, associated with females whose parents have a high-school education (Type 5).

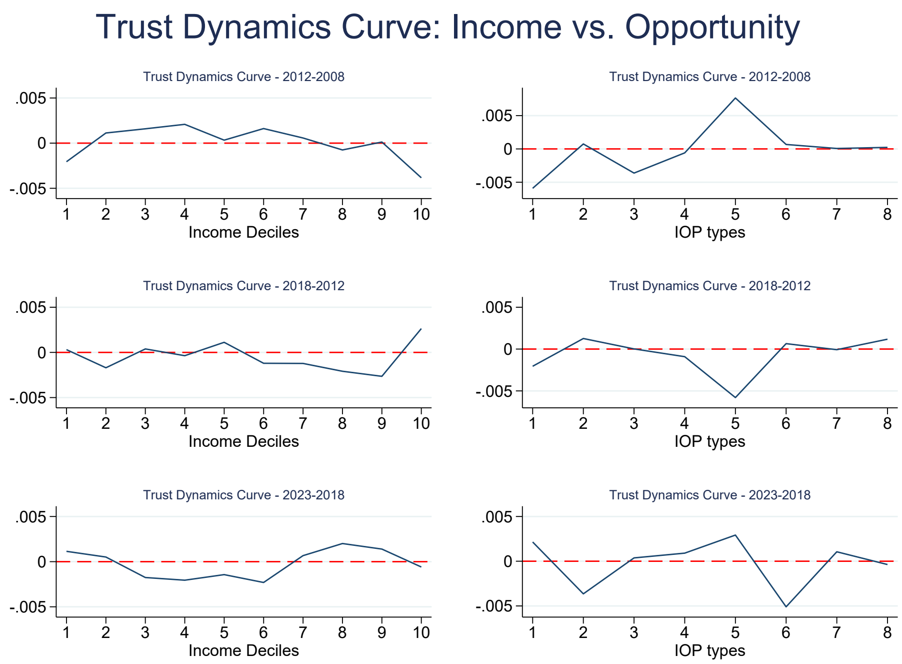

Figure 2.1: *Weighted TDCs for Trust over European Parliament. Socio Economic Status is given by a partition into income deciles (left column) or Eop Types (right column. all the curves are weighted for sub-population size in order to have a more robust comparison. Source: our elaboration from ESS.*

When considering generalized trust (Figure 2.2), broadly similar patterns emerge, although the two crises seem to have generated dynamics opposite to those observed for political trust, particularly when looking at the income-decile partition. Following the 2010 sovereign debt crisis, the recovery in generalized trust appears slightly regressive across income deciles, while the type-based partition suggests a more progressive trend, in contrast with the patterns identified for political trust. At the same time, the recovery of both social and institutional trust among the lowest income deciles may be interpreted as a relatively positive signal, suggesting that the groups most exposed to economic shocks were nonetheless able to regain some trust over time.

During the intermediate period (2018–2012), relative stability is again visible in the income-decile partition, while the type-based classification appears more regressive. A noteworthy difference with respect to political trust is that Type 5—females whose parents attained only a high-school level of education—shows an increase in generalized trust, in contrast to the decline previously noted for political trust in the same group. More generally, the intermediate period points to regressive tendencies, particularly under the type-based partition, with individuals associated with higher parental education levels appearing to experience a relative increase in social capital as measured by their ranking in the distribution of generalized trust.

Finally, in the most recent period (2023–2018), a slightly regressive tendency can be observed, with social trust appearing to increase among individuals at the top of the income distribution.

Overall, these descriptive patterns suggest that generalized trust may be somewhat more stable than political trust when examined across the individual status distribution, a conclusion that is in line with insights from the literature on social capital (Putnam *et al.*, 1994; Kaasa & Andriani, 2022).

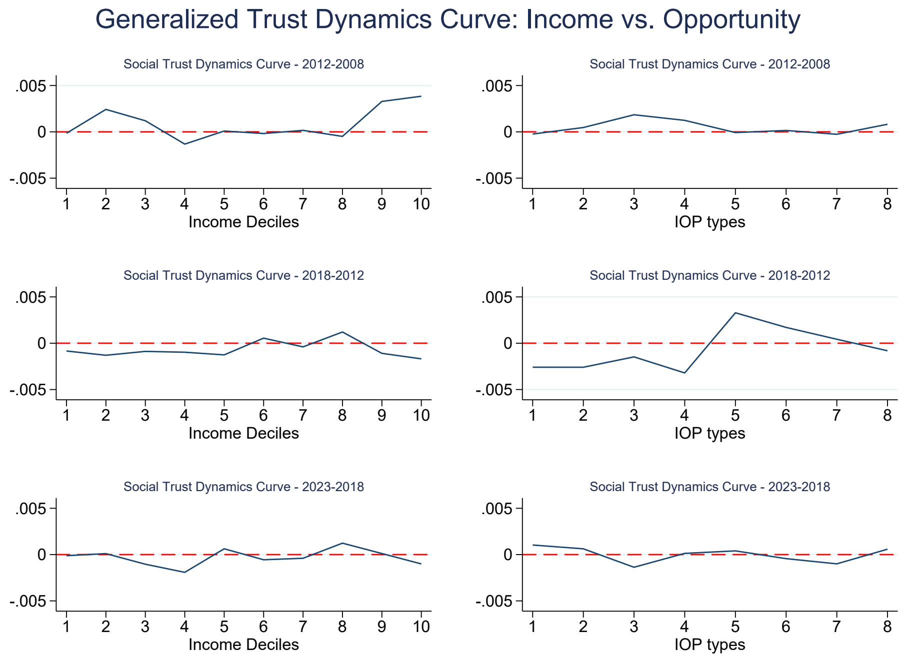

Figure 2.2: *Weighted TDCs for Trust toward others. Socio Economic Status is given by a partition into income deciles (left column) or Eop Types (right column. all the curves are weighted for sub-population size in order to have a more robust comparison. Source: our elaboration from ESS.*

2.4.2 Welfare analysis: Proposition 1 e 3

We now turn to assessing the results from a normative perspective.

As discussed in Paragraph 2.2.1, the TDC is a useful tool for investigating potential increases or decreases in the socioeconomic gradient of the observed dynamics. However, it does not provide direct information about the overall welfare-improving characteristics of the curve itself, which cannot be determined *a priori* and thus requires further investigation.

Building on Propositions 1–3, we formulate normative judgments regarding the curves under analysis. Subsequently, drawing on Propositions 2–4, we extend the comparison across different time spans to derive a normative evaluation of both the curves and the periods considered, which will be discussed in greater detail in Section 2.4.3.

As indicated by these propositions, if subgroup composition remains constant over time or corresponds to equal-sized partitions (as in the case of deciles), a TDC that lies entirely above the zero benchmark line for all selected groups can be interpreted as generating welfare improvements. Since the first assumption is unlikely to hold given the intrinsic zero-sum nature of CDF analysis, welfare changes are instead assessed by focusing on the cumulative version of the TDC curves. For completeness, Proposition 1 is still illustrated in the left panels, even though this replicates the results already shown in Figures 2.1 and 2.2, discussed in Section 2.4.1.

Figures 2.3 and 2.4 show trust patterns in the European Parliament, using income deciles partitions (Figure 2.3) and IOP partitions (Figure 2.4). Figures 2.5 and 2.6 present the same analysis for generalized trust.

When examining political trust, several observations emerge. First, with respect to income deciles, it cannot be clearly stated that the TDC for the period 2012—2008 was welfare-improving. The curve in the left panel of Figure 2.3 appears slightly progressive, yet its cumulative version (right panel) does not remain above zero for all $G \in \mathbb{G}$. A similar descriptive conclusion applies to the subsequent panels, as Proposition 3 does not hold for either the 2018–2012 or 2023–2018 periods.

When considering the partition by *types*, the same conclusion follows: no curve indicates a welfare increase from a normative perspective. Nonetheless, the results for the 2023–2018 period display somewhat more positive signals compared to the earlier intervals.

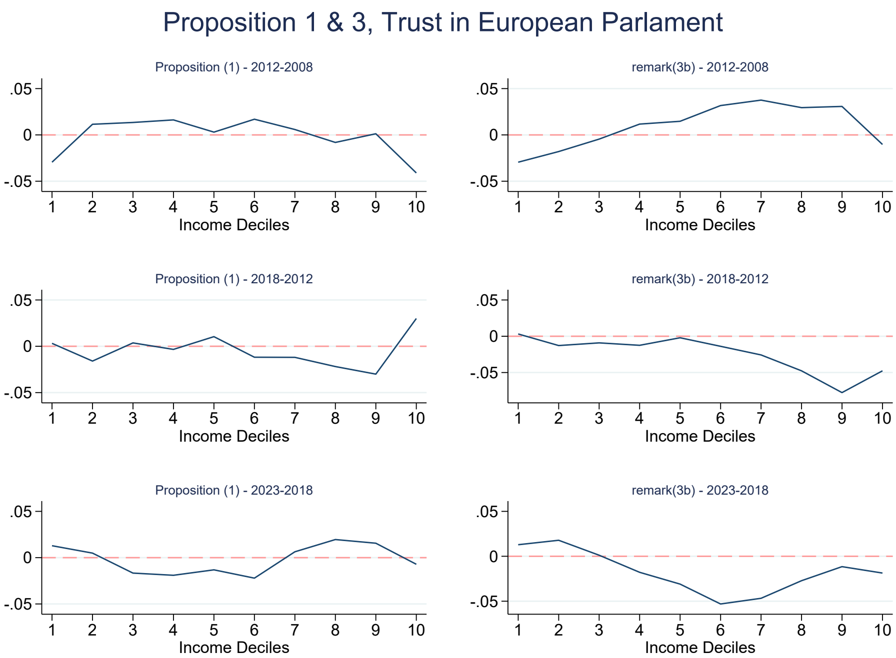

Figure 2.3: *Trust toward European parliament: Proposition (1)-(3). SES groups are defined on income deciles.Source: our elaboration from European Social Survey*

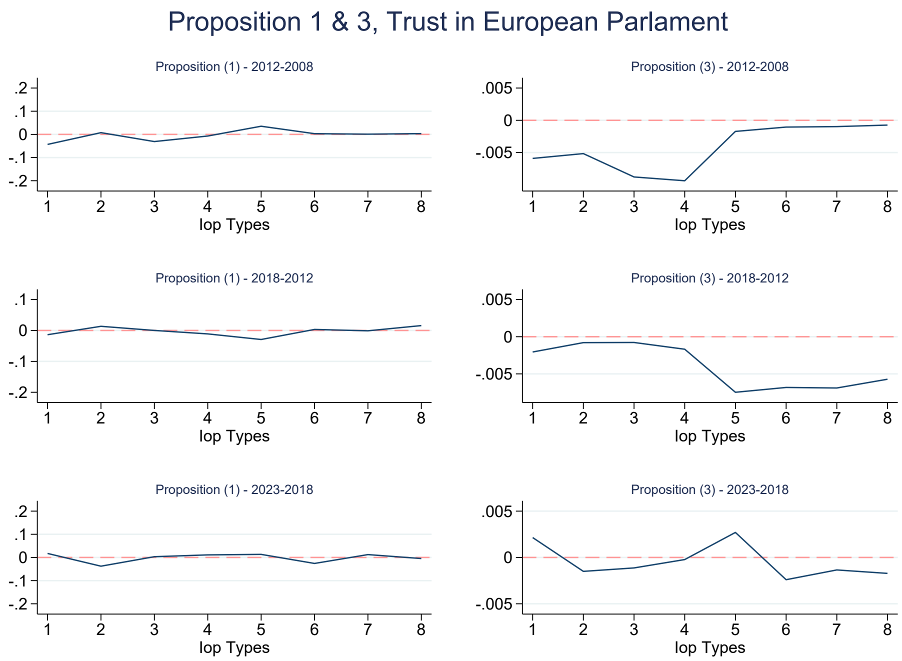

Figure 2.4: *Trust toward European parliament: Proposition (1)-(3). SES groups are defined on IOP Types.Source: our elaboration from European Social Survey*

When examining generalized trust, a different picture emerges. The curves following the sovereign debt crisis suggest a welfare-improving trend for both income deciles (Figure 2.5) and IOP types (Figure 2.6), with both the weighted and unweighted cumulative TDC lying above the zero line.

By contrast, both the middle period (2018–2012) and the post-COVID period display the opposite tendency. The curves for income deciles indicate a steady decline, whereas those based on the *type* partition appear mostly welfare-improving.

Taken together, these patterns highlight the importance of considering both dimensions of inequality, since the conclusions differ depending on whether the focus is placed on income as a final outcome or on inequality of opportunity.

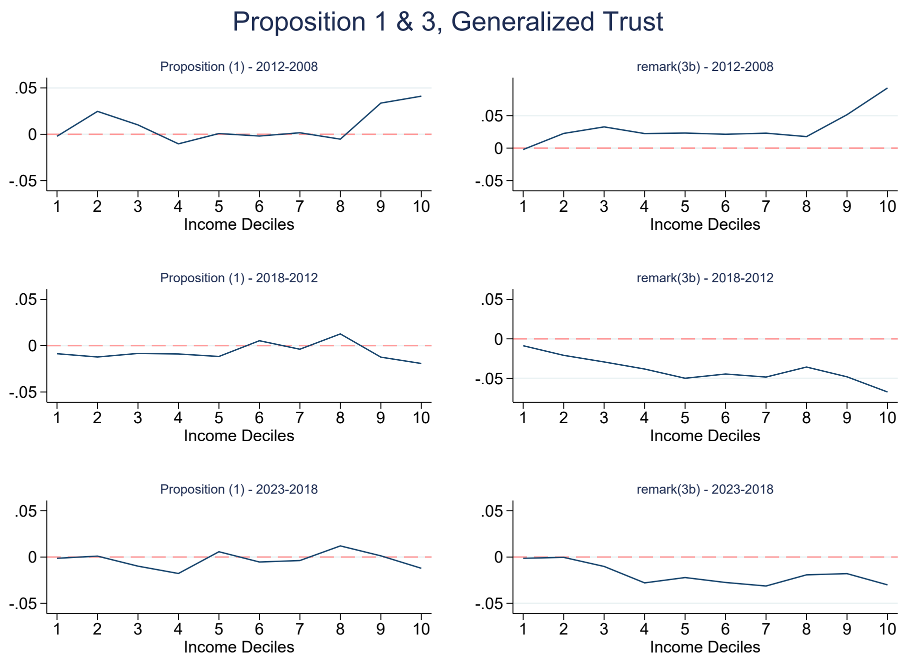

Figure 2.5: *Trust toward others: Proposition (1)-(3). SES groups are defined on income deciles.Source: our elaboration from European Social Survey*

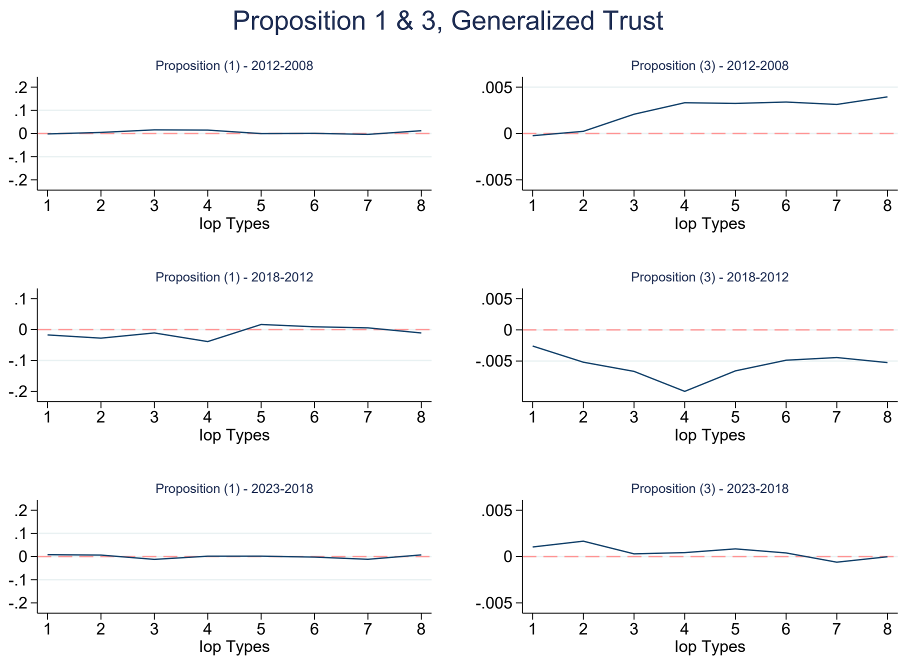

Figure 2.6: *Trust toward others: Proposition (1)-(3). SES groups are defined on EOP Types.Source: our elaboration from European Social Survey.*

2.4.3 Comparison across different periods: Proposition 2 e 4

We now turn to a direct comparison of the curves under analysis, providing a graphical representation of Propositions 2–4. As outlined in the Data section, the comparison focuses on the curves associated with the post-2010 crisis and the COVID-19 pandemic, in order to examine individual responses to European institutions and to others following these two socioeconomic shocks.

From the figures below, several descriptive patterns can be identified. For trust in the European Parliament, no clear dominance emerges, as both the TDCs and their cumulative versions intersect, whether the partition is based on income deciles (Figure 2.7) or on IOP *types* (Figure 2.8). In the case of income deciles, however, the two curves display opposite patterns. The cumulative version (right panel) suggests that the post-2010 TDC comes close to dominating the post-COVID TDC, consistent with the slightly progressive (welfare-improving) tendency shown in the left panel.

However, the results differ when comparing income deciles with IOP types. In particular, the cumulative TDC after the pandemic for the partition based on types (Figure 2.8) appears to lie above the cumulative TDC following the 2008 crisis, with the exception of the two most advantaged types. This suggests that, although no overall dominance can be established, the recovery of generalized trust after the pandemic may have been relatively stronger among disadvantaged groups, pointing to a more inclusive pattern compared to the post-2008 period.

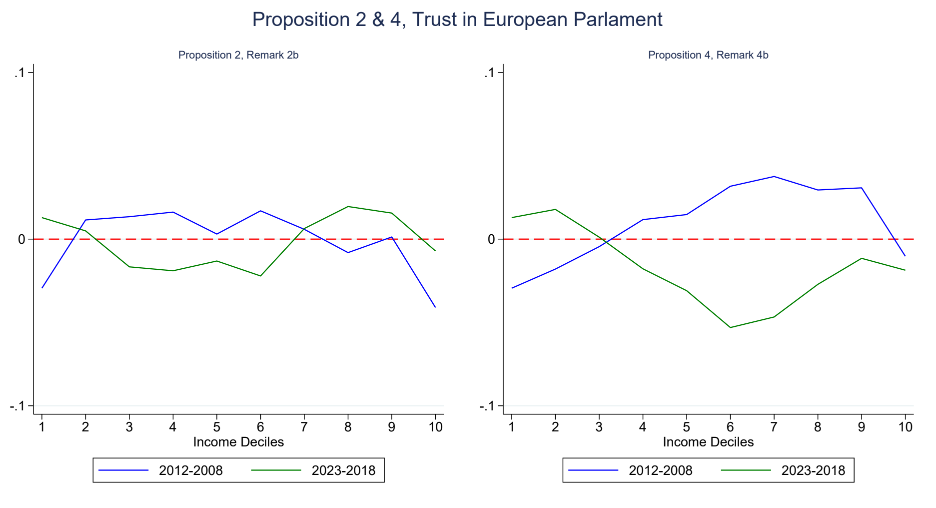

Figure 2.7: *Trust toward european parliament: Proposition (2)-(4). SES groups are defined on income deciles.Source: our elaboration from European Social Survey*

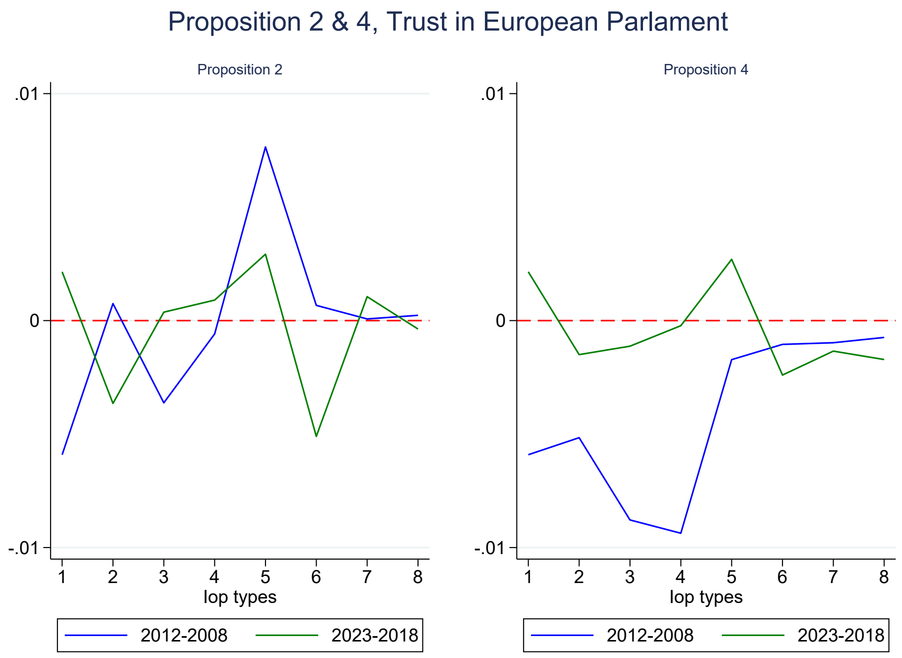

Figure 2.8: *Trust toward european parliament: Proposition (2)-(4). SES groups are defined on IOP Types.Source: our elaboration from European Social Survey*

We obtain more consistent patterns for generalized trust. As shown in Figures 2.9, while the results for Proposition 2 do not indicate clear dominance, the cumulative versions of the curves tell a different story. In particular, the Generalized Trust TDC based on the income-decile partition appears to dominate the alternative across all SES groups. This suggests that the erosion of social capital observed in recent years may also have implied a welfare loss when assessed through the distribution of generalized trust, whereas, according to our model, the post-2010 crisis was instead followed by a welfare-improving increase in trust.

A broadly similar tendency emerges when considering the partition based on types (Figure 2.10). In this case, the post-2010 curve remains above zero for all SES groups and appears to come close to dominating the post-COVID curve, suggesting a relatively stronger recovery of generalized trust after the sovereign debt crisis than after the pandemic. At the same time, both curves lie close to or above zero, indicating some positive signs of recovery across groups.

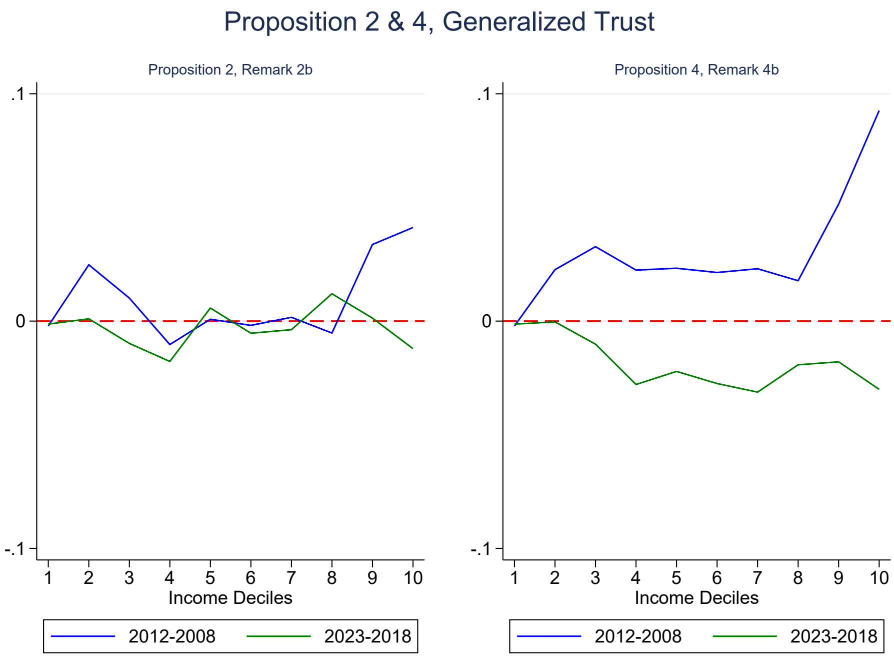

Figure 2.9: *Trust toward others: Proposition (2)-(4). SES groups are defined on income deciles.Source: our elaboration from European Social Survey*

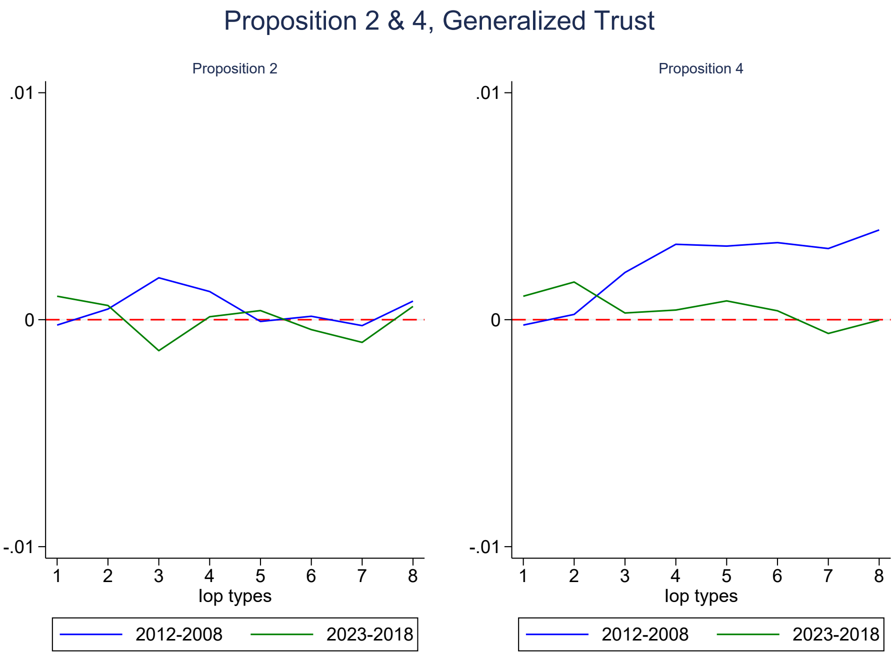

Figure 2.10: *Trust toward others: Proposition (2)-(4). SES groups are defined on IOP Types.Source: our elaboration from European Social Survey*

To sum up, while the specific patterns vary depending on the SES partition and the crisis considered, a common feature emerges across the different analyses. In terms of normative evaluation, all figures indicate a deterioration during the period 2012–2018, suggesting that this phase was marked by a generalized decline in both institutional and social trust across groups. This period therefore represents a turning point in the analysis, as it shows that the erosion of these two core dimensions of social capital was not limited to particular subgroups but instead appears to have been a broader, system-wide phenomenon. At the same time, generalized trust shows somewhat more encouraging signals of recovery in the later periods, whereas trust in government presents a far less favorable picture. Although these findings are purely descriptive, they nonetheless provide useful insights into how the dynamics of trust may have evolved differently across shocks and socioeconomic dimensions.

To examine whether this and other patterns reflect a more general feature beyond trust, in the next section we extend the analysis to an alternative outcome, namely subjective well-being, which is widely used as a proxy for individual utility.

2.5 Alternative outcomes: Subjective well being

Since the Easterlin (1974) paradox, the literature on subjective well-being has flourished (see Clark (2018) for a survey). So far, various studies have explored the counterintuitive relationship between income and happiness. Among them, particular emphasis has been placed on the role of income inequality and socioeconomic status, with evidence yielding mixed results. For instance, Ferrer-i Carbonell & Ramos (2021) find a negative effect of inequality on self-reported life satisfaction using the German SOEP database. Similarly, Georgellis *et al.* (2022), using BHPS data, focuses on the role of occupational status, finding that subjective well-being improves as individuals move up the status ladder.

To our knowledge, Ravazzini & Chávez-Juárez (2018) represents the only study that directly examines the impact of inequality of opportunity on subjective well-being. Using data from the European Social Surveys, they find that the total effect of inequality of opportunity is not significant at the aggregate level but becomes significant when distinguishing individuals by socioeconomic status.

Moreover, they synthesize the distinct impacts that income inequality and inequality of opportunity have on different parts of the distribution. Specifically, they highlight the role of inequality of opportunity at the lower end of the distribution, whereas income inequality primarily affects wealthier individuals due to the fear of losing their position.[16]

In a nutshell, the literature converges on the view that aversion to inequality should be addressed from two complementary perspectives: a normative one, concerning how inequality is perceived to arise, and a positive one, focusing on how inequality affects individual prospects.

In a way, this can also be seen in our descriptive patterns, shown in Figure 2.11. Subjective well-being seems to react more to income deciles than to the opportunity-based partition, as suggested by the larger variation, in magnitude, of the TDCs (now defined in terms of Subjective well-being) in the left panels.

More specifically, the curves for both income deciles display a slightly regressive tendency, suggesting that improvements in subjective well-being may have been concentrated mainly in the upper part of the distribution, with some exceptions during the 2018–2012 period.

[16] More broadly, their paper addresses the identification of which type of inequality is most relevant to individuals, specifically considering who is most concerned and by which type of inequality.

By contrast, the partition based on types reveals more stable patterns, indicating that variations in subjective well-being appear less sensitive to characteristics inherited or deemed beyond individual control.

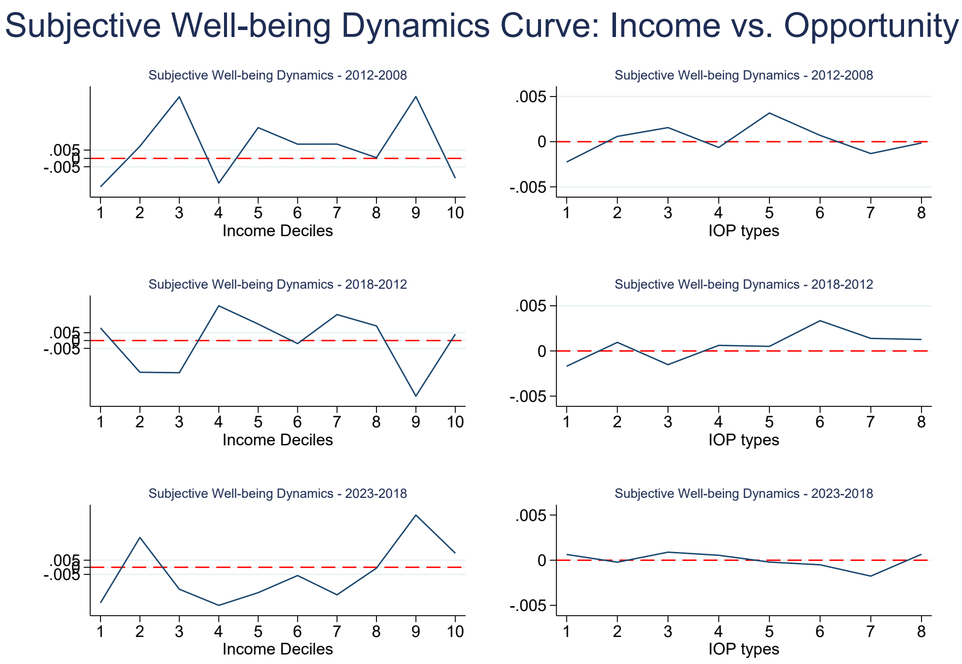

Figure 2.11: *Weighted TDCs for Subjective Wellbeing . Socio Economic Status is given by a partition into income deciles (left column) or Eop Types (right column. all the curves are weighted for sub-population size in order to have a more robust comparison. Source: our elaboration from ESS.*

Moving on to the normative evaluation of the curves, we can instead point out two main observations.

First, when considering both income-decile and IOP-type partitions, depicted in the right panels of Figure 2.12, the increase in subjective well-being after the 2010 crisis appears welfare-improving, as the curves for both Remark 1 and, more consistently, Remark 3 remain above the zero-line benchmark for all $G \in \mathbb{G}$,a results in line with what was found in figure 2.5.

By contrast, in the subsequent years no clear signs of welfare improvement emerge when SES are partitioned into types.

When focusing on the income-decile partition (Figure 2.13), a modest welfare increase can be observed in the years following the 2010 crisis, whereas no improvement is detectable in the later periods.

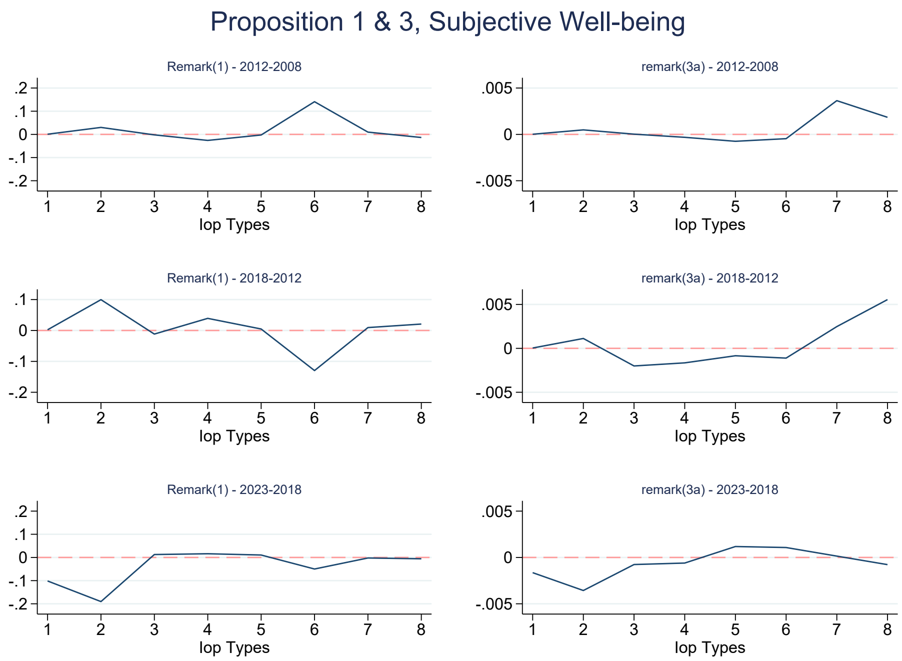

Figure 2.12: *Subjective Well-being: Proposition (1)-(3). SES groups are defined on income deciles.Source: our elaboration from European Social Survey*

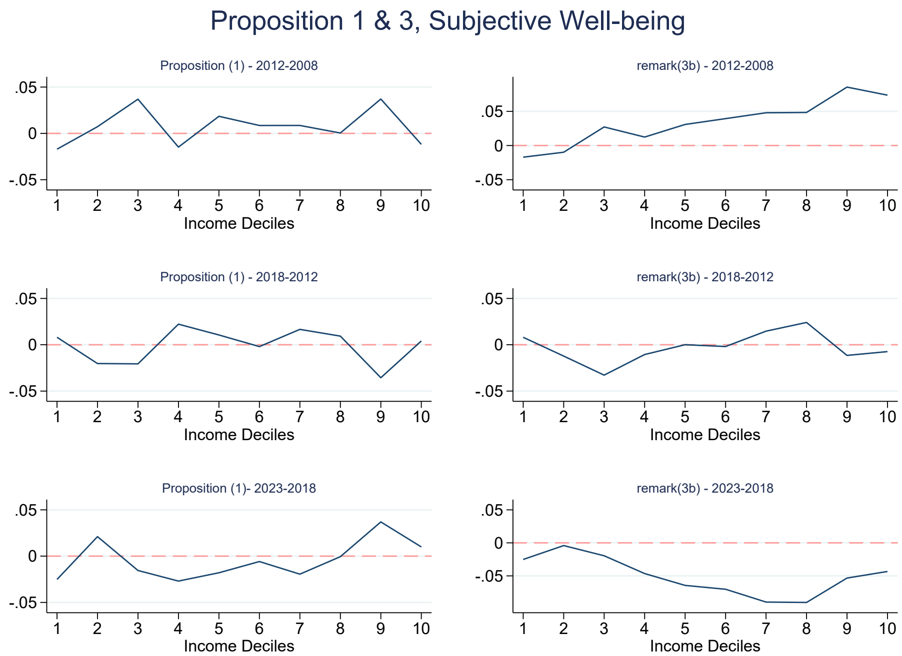

Figure 2.13: *Subjective Well-being: Proposition (1)-(3). SES groups are defined on IOP Types.Source: our elaboration from European Social Survey*

Finally, when directly comparing the TDCs across different periods, it can be observed that for income deciles the 2012–2008 curve appears to come close to dominating the 2023–2018 curve, with the sole exception of the second decile. By contrast, when considering the partition based on equality of opportunity, no clear dominance emerges.

These results appear broadly consistent with those obtained for generalized trust, as shown in Figures 2.9 and 2.10, and may indicate that trust and subjective well-being share similar components, potentially representing different dimensions of the same underlying construct. For further robustness, we repeat the analysis on self-declared happiness, as shown in the appendix. Specifically, similar patterns emerge when focusing on the general pattern of the curves (figure 2.16) and on the different propositions (Figures 2.17, 2.18, 2.19 and 2.20), all shown in the appendix. By contrast, the results for trust in the European Parliament appear to reveal different patterns, suggesting the need for additional evidence and further investigation.

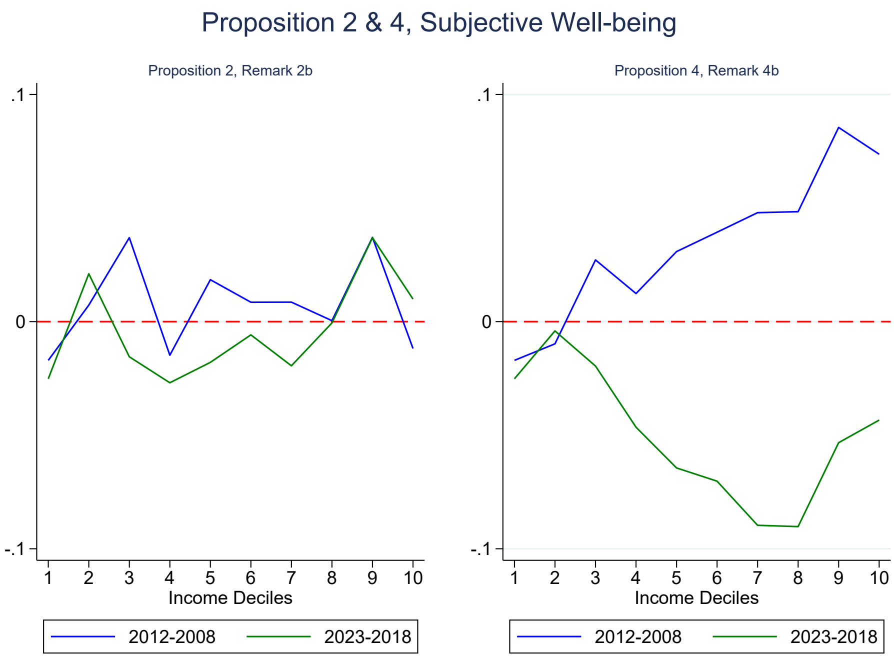

Figure 2.14: *Subjective Well-being: Proposition (2)-(4). SES groups are defined on income deciles.Source: our elaboration from European Social Survey*

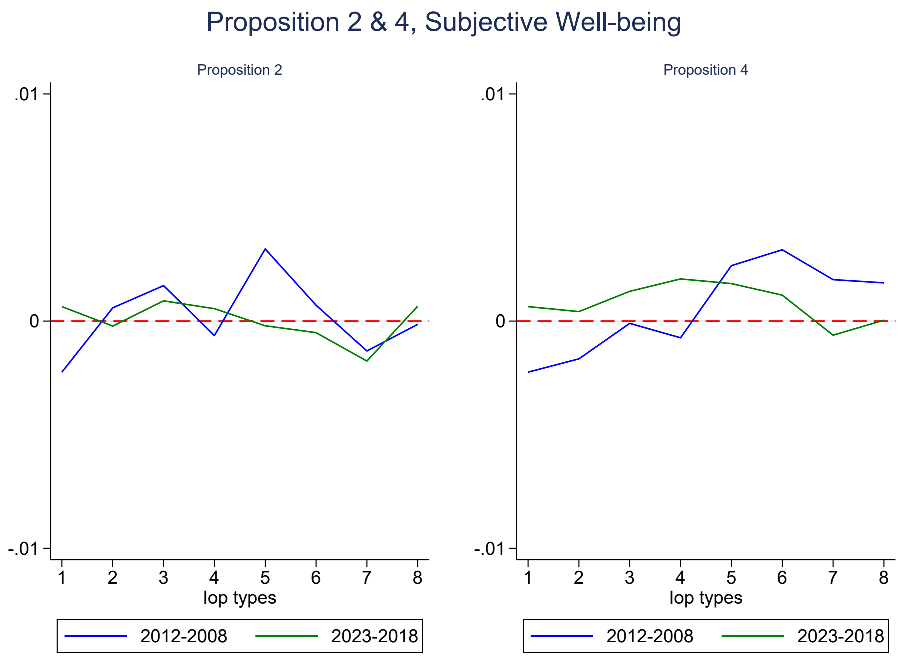

Figure 2.15: *Subjective Well-being: Proposition (2)-(4). SES groups are defined on IOP Types.Source: our elaboration from European Social Survey*

2.6 Conclusion

In this study, we have presented a novel approach to analyzing trust dynamics and their impact on different segments of the population, namely the Trust Dynamics Curve (TDC). This method provides a consistent measurement of trust variations across socio-economic groups, regardless of whether trust indicators are expressed on a cardinal or ordinal scale. In doing so, it addresses key methodological challenges arising from the categorical nature of these variables. However, while TDCs serve as a valuable graphical tool, a proper welfare evaluation requires a more structured framework. To this end, we proposed a theoretical model designed to deliver a more comprehensive assessment of trust trends.

Building on this model, we introduced a normative characterization of the derived TDCs. This framework allows for a comprehensive evaluation of changes in trust levels, capturing not only their distributional dynamics but also their welfare implications, as it incorporates a normative assessment of the SES partition.

We applied this framework to ESS data to analyze trust dynamics across the European population as a whole. This descriptive analysis primarily aimed to illustrate how trust variations are influenced by individual characteristics and how different subgroups experienced changes in trust following the various economic downturns that have occurred over the past 20 years.

Our findings reveal some degree of heterogeneity in trust dynamics, highlighting the importance of considering multiple individual factors when defining socioeconomic groups.

When examining institutional trust, the results suggest a strong impact of recent crises on citizens' confidence in European institutions. Trust in the European Parliament has followed a persistent downward trend, with marked declines after both the 2010 sovereign debt crisis and the COVID-19 pandemic. Although trust erosion appears widespread, its distribution across socioeconomic groups seems uneven. In particular, individuals in the middle-income deciles appear to have been most affected in the aftermath of the pandemic, while in terms of *types* the steepest declines are observed among individuals whose parents have low educational attainment.

Moreover, the evidence indicates that the downward trajectory observed after 2012 has not been reversed, in line with earlier findings from the literature. Our model, however, adds an additional perspective by suggesting that this decline may have been regressive, thereby pointing to continued welfare deterioration and highlighting the long-term effects of the sovereign debt crisis.

A slightly different pattern emerges for social trust. The 2010 crisis appears to have affected institutional trust more severely, while social trust displayed a progressive trend during the same period, with indications of welfare improvement. This relatively positive trajectory, however, did not persist. Both in the intermediate period (2012–2018) and in the aftermath of the COVID-19 pandemic, social trust experienced a downturn, with welfare losses that show little evidence of recovery, regardless of whether groups are defined by income deciles or by types.

To test the robustness of our results and to provide a complementary perspective on the dynamics of social capital, we also examined subjective well-being (SWB) as an alternative outcome.

Overall, the findings are broadly consistent across the two dimensions of social trust and SWB, reinforcing the view that they represent closely related and complementary aspects of social capital. In line with the literature, social trust appears less volatile than income-related components and therefore tends to display greater persistence over time. SWB, by contrast, follows broadly similar trends but is more sensitive to income variation and more volatile in response to changing economic conditions.

Taken together, these results suggest that, while social trust and SWB differ slightly in their responsiveness to economic shocks, both dimensions reflect common underlying patterns in how individuals experience and evaluate their social and economic environment.

Future research can build on these findings in several ways. Theoretically, an important extension would involve developing a measurement model capable of tracking intertemporal trust dynamics, taking into account historical trends beyond just the initial and final periods. Empirically, applying our approach to specific countries could offer deeper insights into the effectiveness of trust-related policies. By comparing Trust Dynamic Curves (TDCs) across different nations and contexts, researchers can gain indirect evidence on the role of institutions and policies, including factors such as access to universal trust-building programs and institutional transparency.

Overall, our study highlights the need for policies aimed at rebuilding trust in both institutions and society at large. Given the crucial role of trust in fostering economic and social stability, addressing disparities in trust dynamics should be a priority for policymakers seeking to enhance civic engagement, social cohesion, and long-term well-being across European societies.

In addition, our framework makes it possible to uncover heterogeneities across different socioeconomic groups, showing how trust dynamics may vary substantially depending on the chosen classification. This perspective is essential to fully capture the societal impact of changes in trust, as the distinction between regressive and progressive patterns largely depends on the criteria used to define socioeconomic groups.

Finally, the proposed approach also provides additional tools to assess the impact of major economic downturns on trust, such as the COVID-19 pandemic or the sovereign debt crisis. Understanding these heterogeneous effects can help anticipate broader patterns in civic engagement and social cohesion, offering valuable insights for policymakers to design more effective supra-national strategies that specifically target the groups most affected by declining trust levels.

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2.7 Appendix

Table 2.3: *Percentage distribution of responses by country and ESS round*

Country	**2008**	**2012**	**2018**	**2022**	**Total**
AT	-	-	7.00	7.57	3.94
BE	8.28	5.94	5.03	5.14	5.90
BG	-	5.88	4.72	-	3.00
CY	-	3.06	2.09	2.05	1.96
CZ	7.77	4.73	5.36	-	4.30
DE	11.29	7.81	6.56	7.50	8.00
DK	7.30	4.90	4.38	-	3.97
EE	-	5.74	5.88	-	3.31
ES	7.57	5.34	3.65	6.04	5.42
FI	-	7.59	5.51	5.94	5.18
FR	9.11	5.71	5.03	5.40	6.06
GR	-	-	-	6.16	1.53
HR	5.45	-	4.53	4.29	3.40
HU	5.53	4.69	3.13	6.64	4.87
IE	-	6.22	4.86	5.68	4.54
IT	-	1.95	5.07	7.47	3.88
LT	-	4.65	4.42	3.89	3.54
LV	7.31	-	2.07	-	1.95
NL	7.84	5.17	4.14	5.41	5.41
PL	6.28	4.58	2.87	4.00	4.24
PT	4.37	3.16	2.62	3.92	3.41
RO	6.81	-	-	-	1.25
SE	-	5.30	4.48	4.38	3.86
SI	5.09	3.16	3.81	4.14	3.95
SK	-	4.44	2.79	4.37	3.12
Total	100.00	100.00	100.00	100.00	100.00

Notes: Distribution of responses by country and ESS round of the analysis. Source: European Social Survey.

Table 2.4: *Trust in the European Parliament by Income Deciles*

Deciles	No trust	1	2	3	4	5	6	7	8	9	10
Survey Year: 2008											
1	136	70	109	122	121	236	98	108	99	36	35
2	208	112	176	175	170	363	156	113	90	53	27
3	195	117	179	228	228	442	210	185	142	30	30
4	192	117	187	257	231	496	254	199	153	43	22
5	145	87	155	221	205	404	246	196	108	38	24
6	108	89	112	191	181	371	218	178	91	41	18
7	102	72	106	177	184	390	230	187	140	28	18
8	83	62	89	145	191	332	257	217	117	52	23
9	75	64	95	163	160	364	256	230	155	53	24
10	56	58	78	143	151	331	282	239	164	55	17
Survey Year: 2012											
1	396	160	205	254	268	493	210	205	131	46	51
2	350	165	234	297	286	599	277	237	146	50	33
3	288	165	237	314	299	540	282	269	151	55	25
4	282	146	252	305	296	561	352	295	161	47	24
5	224	166	251	323	335	552	327	271	170	50	36
6	197	128	224	291	289	560	333	288	178	43	31
7	169	135	182	273	291	550	389	328	190	38	32
8	157	108	148	241	307	501	329	324	194	58	31
9	102	110	127	230	263	455	359	306	201	46	26
10	105	85	149	238	266	441	328	318	197	57	25
Survey Year: 2018											
1	338	168	202	247	216	461	256	206	174	66	52
2	359	201	242	281	303	546	279	266	200	82	57
3	295	162	248	305	301	560	347	289	207	85	51
4	295	155	279	284	305	605	347	313	200	85	47
5	255	161	219	318	321	593	406	358	215	69	35
6	220	130	195	284	318	559	425	325	229	79	55
7	194	140	201	275	299	600	420	393	211	80	29
8	178	106	203	255	317	531	445	430	214	77	21
9	124	88	163	219	246	514	425	358	205	50	25
10	111	73	121	189	242	403	377	391	261	41	34
Survey Year: 2022											
1	179	81	110	144	130	276	147	143	119	26	34
2	225	108	164	199	205	377	224	197	151	50	48
3	229	128	208	229	246	481	284	249	187	61	30
4	216	134	201	267	270	450	351	284	182	74	32
5	195	126	214	303	282	450	319	319	192	53	33
6	220	144	186	266	294	481	375	327	209	83	35
7	167	109	188	258	320	528	377	420	248	68	27
8	156	80	147	257	268	509	422	433	265	72	33
9	116	56	117	182	218	355	335	339	215	69	19
10	115	81	116	182	185	336	341	360	244	85	25

Notes: Number of individuals in each category by decile and by round of the survey. Source: author's elaboration from European Social Survey.

Table 2.5: *Trust in the European Parliament by Iop Types*

Deciles	No trust	1	2	3	4	5	6	7	8	9	10
Survey Year: 2008											
Type 1	222	102	149	214	252	610	274	231	160	52	26
Type 2	137	98	140	166	171	398	232	185	77	33	21
Type 3	178	106	160	213	187	430	259	202	139	66	33
Type 4	120	78	112	160	137	317	197	132	93	33	25
Type 5	255	185	295	411	434	817	470	407	247	85	53
Type 6	288	193	312	412	413	700	407	361	291	84	57
Type 7	47	39	50	113	119	239	195	173	129	36	8
Type 8	53	47	68	133	109	218	173	161	123	40	15
Survey Year: 2012											
Type 1	446	214	360	413	456	817	395	358	216	59	35
Type 2	207	129	204	289	292	486	282	246	140	41	28
Type 3	412	208	289	365	396	738	399	327	181	53	50
Type 4	256	106	166	238	231	431	264	212	115	23	32
Type 5	318	265	409	587	606	1070	641	575	343	120	60
Type 6	443	310	373	560	533	956	601	504	323	88	58
Type 7	81	67	96	156	196	385	322	308	208	60	26
Type 8	107	69	112	158	190	369	282	311	193	46	25
Survey Year: 2018											
Type 1	351	183	290	324	359	728	420	345	209	82	58
Type 2	228	161	226	303	271	537	321	266	176	79	50
Type 3	368	153	221	305	339	604	396	328	207	65	54
Type 4	214	136	228	224	244	431	281	236	124	45	32
Type 5	439	308	453	577	661	1257	817	725	481	156	85
Type 6	531	274	436	580	601	976	718	617	403	134	66
Type 7	112	77	94	164	199	457	388	449	265	81	25
Type 8	126	92	125	180	194	382	386	363	251	72	36
Survey Year: 2022											
Type 1	271	141	252	317	321	598	333	337	220	71	47
Type 2	211	116	157	251	248	435	319	279	146	55	28
Type 3	285	118	215	278	266	503	375	281	197	55	29
Type 4	204	98	173	232	196	365	269	218	163	35	26
Type 5	309	217	330	486	545	965	715	694	435	137	60
Type 6	385	243	365	449	489	794	547	571	374	118	61
Type 7	61	46	79	132	180	331	301	375	265	90	34
Type 8	92	68	80	142	173	252	316	316	212	80	31

Notes: Number of individuals in each category by Eop Types and by round of the survey. Source: author's elaboration from European Social Survey.

Table 2.6: *Deciles size across ESS round*

Deciles	2008	2012	2018	2022	Total
1	6.97	9.63	8.83	6.12	8.04
2	9.78	10.65	10.42	8.59	9.91
3	11.83	10.45	10.55	10.28	10.69
4	12.81	10.83	10.79	10.85	11.19
5	10.89	10.77	10.92	10.96	10.88
6	9.52	10.20	10.43	11.55	10.48
7	9.73	10.26	10.52	11.95	10.66
8	9.34	9.55	10.28	11.65	10.25
9	9.76	8.86	8.95	8.91	9.06
10	9.37	8.80	8.30	9.13	8.84
Total	100.00	100.00	100.00	100.00	100.00

Notes: deciles numerousity and relative size over the ess round under analysis. Source: author's elaboration from European Social Survey.

Table 2.7: *Types size across ESS round*

Deciles	2008	2012	2018	2022	Total
1	13.65	15.01	12.40	12.82	13.45
2	9.87	9.33	9.69	9.90	9.68
3	11.75	13.61	11.25	11.47	12.04
4	8.36	8.26	8.13	8.73	8.35
5	21.79	19.88	22.06	21.58	21.29
6	20.95	18.91	19.75	19.38	19.65
7	6.84	7.59	8.55	8.35	7.92
8	6.79	7.41	8.17	7.77	7.61
Total	100.00	100.00	100.00	100.00	100.00

Notes: types numerousity and relative size over the ess round under analysis. Source: author's elaboration from European Social Survey.

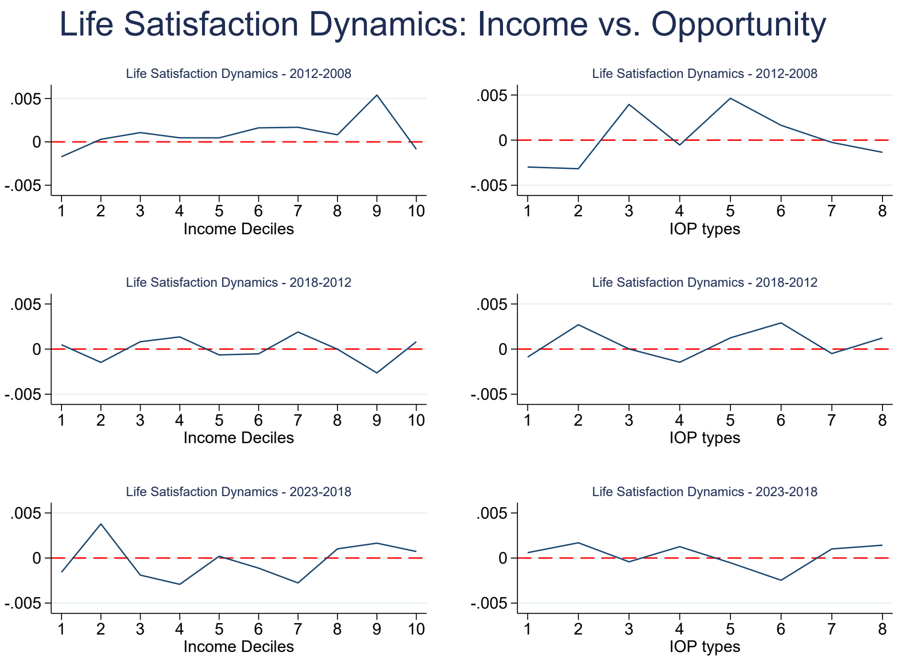

Figure 2.16: *Weighted TDCs for Trust over Life satisfaction. Socio Economic Status is given by a partition into income deciles (left column) or Eop Types (right column). all the curves are weighted for sub-population size in order to have a more robust comparison. Source: our elaboration from ESS.*

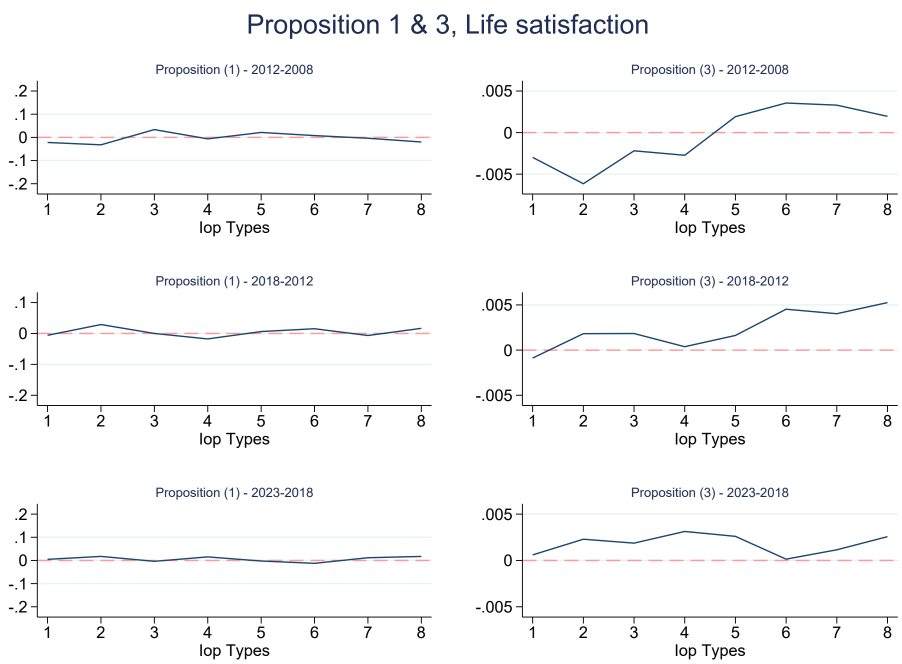

Figure 2.17: *Life satisfaction: Proposition (1)-(3). SES groups are defined on IOP Types.Source: our elaboration from European Social Survey*

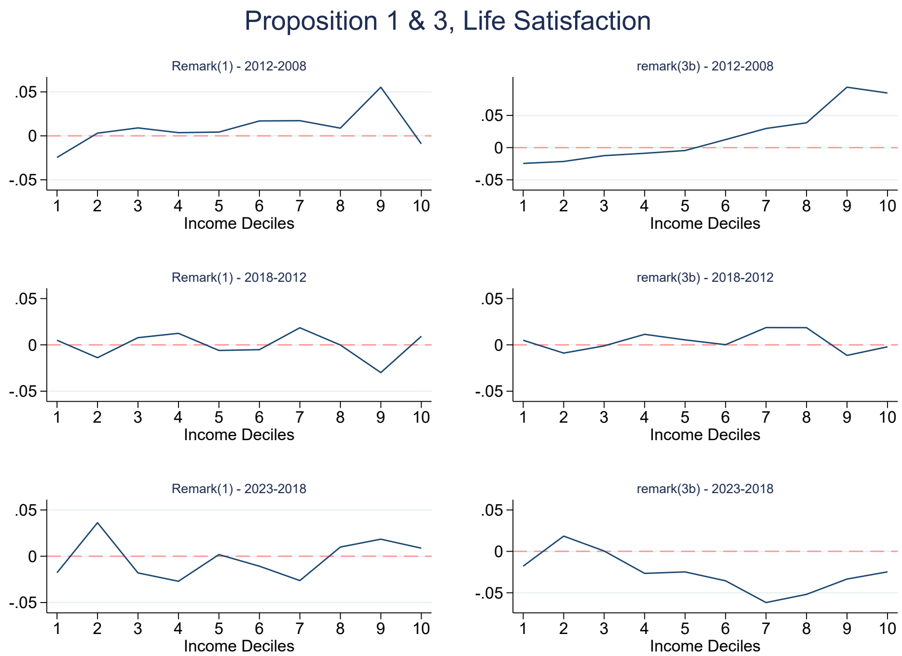

Figure 2.18: *Life satisfaction: Proposition (1)-(3). SES groups are defined on Income deciles.Source: our elaboration from European Social Survey*

Figure 2.19: *Life satisfaction: Proposition (2)-(4). SES groups are defined on Iop Types.Source: our elaboration from European Social Survey*

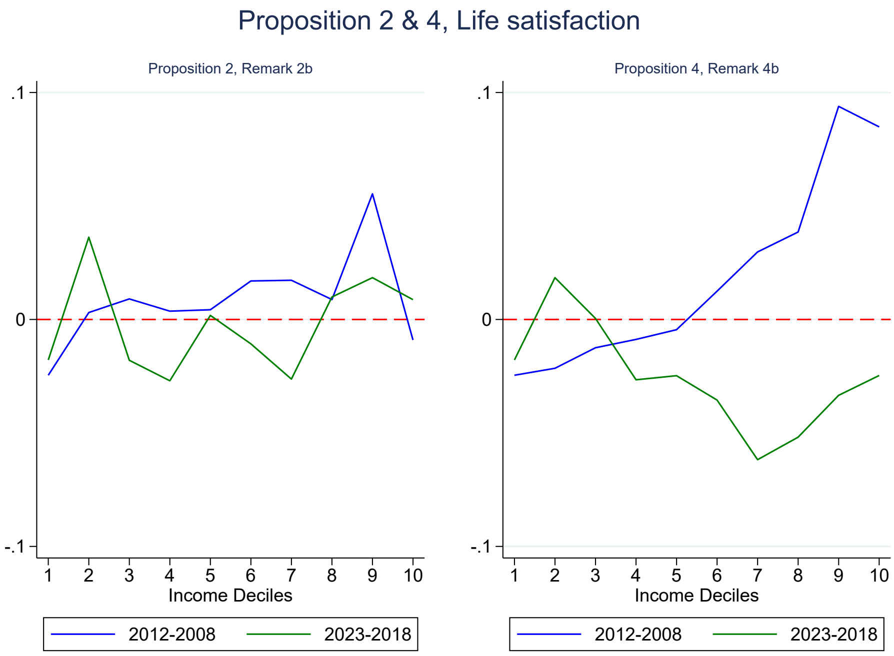

Figure 2.20: *Life satisfaction: Proposition (2)-(4). SES groups are defined on Income deciles.Source: our elaboration from European Social Survey*

Chapter 3

Equality of Opportunity and Responsibility:

An Individual Measure for Sensitivity to effort

Matteo Sabatini[1]

Abstract

The equality of opportunity literature has explored different approaches to quantify inequality arising from factors beyond individuals' control, emphasizing how socioeconomic achievements are shaped by both background circumstances and individual effort. Building on Roemer's Identification Assumption (RIA), this work proposes a measure of individual (local) sensitivity to effort, aimed at quantifying the extent to which individuals can influence their outcomes through effort, conditioned by their circumstances. Formally, this represents the local-steepness of the inverse CDF, which we derive using adaptive kernel density estimations for the type-specific outcome distribution. We then apply this measure to the first wave of the UK Understanding Society, presenting results for both total and labor income.

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3.1 Introduction

The theory of equality of opportunity (EOp) is based on the idea that an individual's outcome is determined by factors for which he is responsible (efforts) and factors for which he is not responsible (circumstances).

According to this literature, whose philosophical foundations are in Rawls (1971); Dworkin (2018); Sen (1985); Cohen (1989), an equitable society is based on two fundamental ideas: (1) differences in outcome that are due to differences in exogenous circumstances are compensated (*compensation principle*) and (2) efforts are adequately rewarded (*reward principle*). In other words, the "ideal" situation or benchmark is not perfect equality per sè, as in the measurement of inequality of outcome, but a "fair" distribution where, after leveling the field of initial circumstances, only disparities due to efforts remain.

Inspired by this debate, many authors proposed formal economic models of equality of opportunity, which are mainly based on the definition of *opportunity sets* and aim at assessing differences in outcomes that are consequences of differences in exogenous characteristics(Fleurbaey, 1994, 2007; Van de Gaer, 1993; Roemer, 1993, 1998), thus focusing on the joint distribution of achievements and observable advantages that individuals have as background circumstances (Ferreira & Peragine, 2013).[2]

More formally, the framework can be defined as follows. Let $N = \{1, \dots, n\}$ denote the population of individuals. For each individual $i \in N$, we observe the outcome $y_i \in \mathbb{R}_+$, the vector of circumstances $c_i \in C = C^1 \times \cdots \times C^{n_C}$, where C^k, $k \in \{1, \dots, n_C\}$, is the set of possible values for circumstance k, and the vector of efforts $e_i \in E = E^1 \times \cdots \times E^{n_E}$, where E^l, $l \in \{1, \dots, n_E\}$, is the set of possible values for effort l. Thus, each individual i is fully characterized by the triple $(y_i, c_i, e_i) \in \mathbb{R}_+ \times C \times E$, and we can assume that

$$y_i = f(c_i, e_i) \text{ with } f : C \times E \to \mathbb{R}^+, \tag{3.1}$$

such that individuals with the same circumstance and same effort obtain the same level of income.[3]

Then, following Roemer (1993, 1998), we can define a *Type* as a set of people having the same Circumstances and, following Peragine (2004), we can define a *Tranche* as a set of people exerting the same levels of Efforts.

Using this structure, we can further define a person's *opportunity set* as the set of all possible achievement levels y he can reach, given his background circumstances c_i (Van de Gaer, 1993). Hence, with this perspective, inequality of opportunity would be eradicated if everyone had opportunity sets with equal values, thus shifting the issue to the proper measurement of the space of opportunity with observational data.

With respect to this, this literature has come up with different measures and results[4], both at an

[2] More specifically, the concept behind the indirect approach, which is at the basis of this work, is to model opportunities as the set of potential outcomes given the exogenous background of individuals, and from which individuals can obtain different achievements depending on their chosen level of effort (or responsibility).

[3] Hence, the model will represent a reduced form for income generating function, which does not consider other factors playing a role and where each can be each C^k and E^l can be finite or not.

[4] These differences in the results are mainly due to the vast array of different methods and approaches, which

aggregate (most of the literature) and at the individual level, research which is lately increasing thanks to the growing availability of data on a granular basis, and that is at the core of our analysis.

In this debate, we argue that one could be interested not only in how much an outcome is determined by background circumstances, but also, and consequently, to what extent individuals have control over their achievements given their types and, hence, how much they can change their outcome by varying their effort levels.

Specifically, if for each individual in our population we have the triple (y_i, c_i, e_i), we argue that the *opportunity set* that individuals face will be indicative of how much individuals are in control of their outcomes given their types.

Moreover, we assert that how much individuals can change their outcomes by changing their degree of effort could be not only interesting per sè, but it could also represent a further source of unfairness. In fact, if we take two individuals belonging to different types and we notice that they can experience different changes in outcomes by exerting the same change in effort, we could be highlighting another aspect of inequality of opportunity, namely those disparities in *Sensitivity to effort* that depend on background circumstances (and that are then unfair).

This work will attempt to quantify these disparities, by first proposing a measure of individual (local) *Sensitivity to effort* that is consistent with the literature on inequality of opportunity and then by applying it empirically to different individual outcomes.

To do so, we will first start with the proper choice of circumstances and effort variables to include in our analysis, following Roemer (1998) both in the definition of types and in the identification of effort, which will be based on the author's Identification Assumption (RIA).

Holding on to this concept, we will then obtain a quantitative measure of how much an individual can change her outcome by changing her effort, depending on her type.

The paper is structured as follow. In section 3.2 we formally define this measure as a local *Sensitivity to effort*, describing the formal steps to obtain it. In section 3.3 we move on to the empirical application, first describing the data in subsection 3.3.1 used for the outcome and the circumstances under analysis and then the methodology used to visualize *opportunity sets* in subsection 3.3.2. We show some of the results in subsection 3.3.3 and provide robustness in subsection 3.3.4. section 3.4 concludes.

are reassumed in the surveys of Ramos & Van de Gaer (2016, 2021)

3.2 From The Roemer Assumption to local Sensitivity to effort

When measuring the degree of inequality of opportunity in a certain society, literature has put particular emphasis on a proper measurement of both circumstances and effort variables, which the authors have addressed in different ways depending on data availability and the specific aim of the study.

In principle, the set of circumstances that should be included shall reflect the concept of "beyond individual's control", hence depicting exogenous characteristics that the society rewards differently and for which people shall not be held responsible for (Ferreira & Gignoux, 2011).

With regard to this principle and for the aim of our measure of local Sensitivity to effort, we follow the definition of Roemer (1993), treating characteristics such as gender, ethnicity and family background as circumstances.[5]

Consequently, with circumstances representing the non-responsibility characteristics of individuals, effort will describe what is in the realm of people's choices and tastes.

Typically, the variables used depend on the case study the authors were dealing with, and reflect human capital accumulation and labor supply decisions in income/wage studies, or variables related to health behavior (such as smoking activities) in health studies.

However, since these variables are very difficult to isolate from circumstances (as, for instance, the choice of getting a higher degree is strongly correlated with the family background of the individuals), the debate regarding both definitions and measures of effort variables is ongoing, especially considering both data availability (usually scarce when looking at these kind of variables) and the need of a concrete definition of what responsibility is.

Consequently, the literature agrees that when effort variables are not observed or cannot be disentangled from circumstances, this can only be addressed with some auxiliary hypotheses.

The most elegant way to obtain effort comes from (Roemer, 1993, 1998), whose Identification of effort has been widely used in empirical work to derive partial inequality of opportunity orderings (Peragine, 2002; Rodríguez, 2008) and that is the starting point for the measure we derive in this work.

In detail, let us consider a set of types[6] and assume that effort is represented by a one-dimensional variable, i.e. $n_E = 1$ and $E = E^1 = [\underline{e}, \overline{e}]$. Then, Roemer's Identification Assumption (RIA) can be stated as follows:

Proposition 1. *Individuals who occupy the same percentile of the outcome distribution, conditional on their type, are assumed to have exerted an equal amount of effort.*

This assumption can be derived from more fundamental hypotheses about the outcome-generating process and the distribution of circumstances and effort and, as Fleurbaey (1995) pointed, RIA is based on two key (and perhaps strong) assumptions. Define $T = \{t \in C^1 \times \cdots \times C^{n_C}\}$ as the possible set of types and let us suppose that for each $t \in T$ we can derive the outcome of the individuals belonging to that type in function of their effort. Hence, because of

[5] The literature has addressed different method to define circumstances, including machine learning methods (Brunori *et al.*, 2023a) and Latent class technique proposed by Li Donni *et al.* (2015); Brunori & Neidhöfer (2021), which we discuss in more detail in section 5

[6] The set of types under analysis does not need to be finite (O'Neill, D and Sweetman, O and Van de gaer, Dirk, 2000)

RIA we will then have the following functions:

$$g_t(e) = f(c_i, e) \quad \text{for each } t \in T,$$

with $e \in E$ and $g_t(e) : E \to \mathbb{R}^+$ representing for each individual the outcome in function of her responsibilities given her type.
RIA will then hold if:

1. $g_t(e)$ is strictly increasing function of e. **[Strictly Increasing Assumption]**

2. Denoting $H_t(e) : E \to [0, 1]$ as the cumulative distribution function of effort conditional on an individual's type, then this CDF is independent of t.

$$H_t(e) = H(e), \quad \forall t \in T \qquad \textbf{[Independence Assumption]}$$

While the second assumption aligns with the responsibility-by-control view (Fleurbaey, 1995) and is considered natural for normatively relevant effort, the first assumption could seem quite strong. However, if we think of e as a variable positively related to an individual's desirable achievement, then it becomes more acceptable.
Under the Roemer Identification Assumption, our normative measure of effort becomes the percentile of the outcome distribution conditional on one's type and is, by construction, uniformly distributed over $[0, 1]$ for all types and independently distributed from circumstances. Moreover, it is an ordinal measure of responsibility. Incomes at a given percentile can be compared between types and that allows us to visualize *opportunity sets* for each individual belonging to a specific type.
Using percentiles is a useful tool. In fact, to isolate effort we need to compute the Cumulative Distribution Function (CDF) for each outcome relative to the type and, through the inverse of it (the quantile function), obtain the percentile, within an individual's type outcome-distribution as the relevant measure of her responsibility factor [7] .
More formally, for each type t and outcome y we will have the CDF

$$F_t(y) : \mathbb{R}^+ \to [0, 1],$$

the proportion of individuals of a type who have an outcome $x \leq y$.
Then, if we define $\pi_t = F_t(y)$ as the percentile of a type-specific cumulative distribution function, for each y we will have π_t as the effort needed to obtain income y for someone of type t.
Denoting the *opportunity set* of someone belonging to type t as the potential outcomes achievable by individuals sharing the same characteristics, to visualize such space of opportunity we will

[7] The inverse of the Cumulative Distribution Function will tell us a which percentile of our distribution we can find a certain value, hence if types are non-responsibility characteristics of individuals and we observe the distribution for each one of the possibilities, thanks to RIA we will be able to observe the outcome achieved by individual exerting the same level of responsibility.

need to focus on the inverse of the CDF of effort conditional on the type of belonging:

$$S_t = \left\{ (y, \pi_t) \in \mathbb{R}^+ \times [0,1] : y = F_t^{-1}(\pi_t) \right\},$$

which gives us the combinations of incomes and effort someone of type t can obtain. Here below, in Figure 1, we can see the opportunity sets of a generic *desirable* socio-economic outcome of two generic types. Here, we consider total net monthly income as the outcome variable, while the circumstances defining the types are represented by males with a high parental background versus females with a low parental background.[8] In this example, the type in blue (Type A) clearly represents the most advantaged type, as its curve dominates the red-type (Type B) opportunity sets and, holding constant the level of Roemer effort, it is always reaching higher income values.[9]

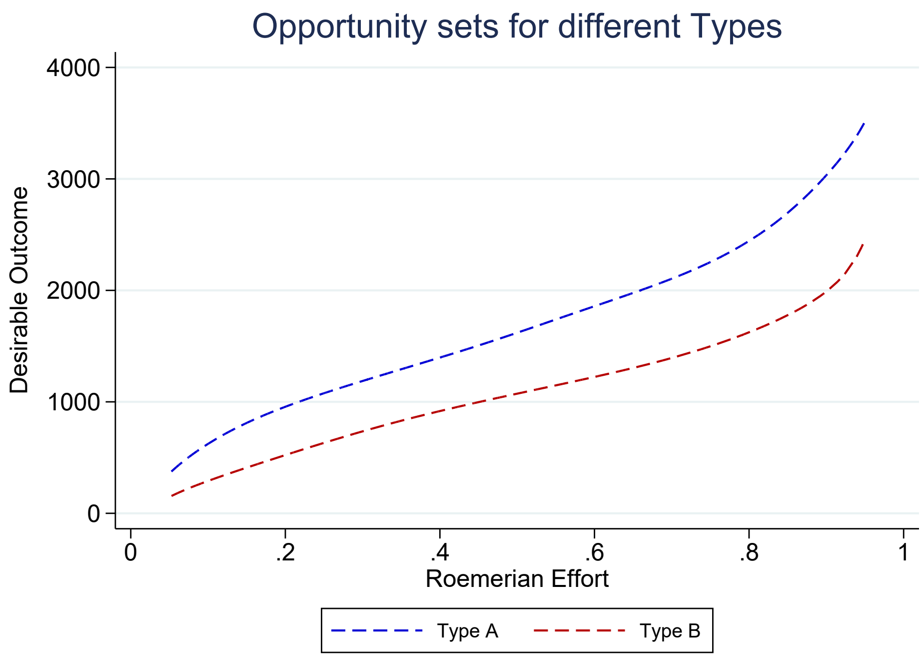


Figure 3.1: *Visualization of Opportunity sets for two generic types. On the X-axis it is shown individual effort obtained through Roemer Identification Assumption. On the Y-axis a generic desirable outcome. Source: Our elaboration from Uk understanding Society(2009-2011).*

Bearing this in mind, we can measure how much,given one's circumstances, the outcome changes when an individual changes her effort level by measuring the point slope of these inverse CDFs.

Formally: if effort is measured as

$$\pi_t = F_t(y) \tag{3.2}$$

[8]A more detailed specification of the variable under analysis is provided in Section 4.

[9]We recall that this is just a simplified version of what Roemer intended, since it just consider a small subset of all the possible observable types.

then the outcome in function of effort will be, using the quantile function:

$$y = F_t^{-1}(\pi_t) \tag{3.3}$$

which can be rewritten, substituting (3.3) into (3.2), as:

$$y = F_t^{-1}(F_t(y)) \tag{3.4}$$

The slope of the outcome with respect to effort will then, for each type t, be given by the first derivative of the inverse CDF with respect to $F_t(y)$.[10]

Mathematically, starting from (3.4) and deriving with respect to y, we have the following:

$$1 = \frac{dF_t^{-1}(F_t(y))}{dF_t(y)} \cdot \frac{dF_t(y)}{dy} \tag{3.5}$$

$$1 = \frac{dy}{d\pi_t} \cdot \frac{dF_t(y)}{dy} \tag{3.6}$$

From which we can obtain the local *Sensitivity to effort* measure as:

$$\textbf{Slope} = \frac{dy}{d\pi_t} = \frac{1}{\left(\frac{dF_t(y)}{dy}\right)} \tag{A}$$

This measure represents the slope of the opportunity set for each individual for each value of π_t. However, we notice that this measure will be sensitive to the unit of measurement, since the measure of effort will always be between 0 and 1 and the outcome of interest measured in different ways depending on the research question.

To overcome this problem, we can derive further measures of the curve steepness, based on the point elasticity instead of the slope and hence measuring how much a percentage change of effort results in a percentage change of the outcome of interest.

Therefore, we will have the measure of the elasticity of our slope:

$$\textbf{Elasticity} = \frac{dy}{d\pi_t} \cdot \frac{\pi_t}{y} \tag{B}$$

The above-mentioned steps lead to a formal definition of the local Sensitivity to effort, measured both in terms of slope and elasticity:

[10] In Section 3.5.1, we replicate the derivation for the case where the outcome variable is preliminarily transformed into logarithmic form.

Definition 1. *The **slope local Sensitivity to effort** is a measure of how much an individual can change his outcome by varying his effort, given his type. Formally, it corresponds to the inverse of the slope of the Cumulative Distribution Function.*

Definition 2. *The **elasticity of local sensitivity to effort** is defined as the percentage variation in an individual's outcome associated with a one percent change in effort, conditional on the individual's type. Formally, it is given by the product of the local sensitivity to effort and the ratio between effort and outcome.*

As we can see from these formal definitions, in order to compute these two measures, we hence need three main ingredients, that is:

- Select the **outcome** (y) on which the measure is to be applied.
- Define **Types** (t) properly to visualize opportunity sets.
- Identifying an efficient and precise method for estimating **smooth and differentiable CDFs** (and the respective PDFs) from observational data.

In the next paragraph, we will derive this measure empirically, describing first the data used for both the outcome and the circumstances used for the types partitioning (subsection 3.3.1) and then focusing on the methodology used to obtain a smooth and differentiable CDF (subsection 3.3.2).

3.3 Empirical Application

3.3.1 Data

To give an illustration of the methodology discussed above, we apply it to the first Wave of of the UK Understanding Society dataset (2009-2011). Understanding Society, the UK Household Longitudinal Study, is a survey of approximately 40,000 households in the UK, that started in 2009. Households are visited annually to track changes in their conditions through face-to-face interviews or online surveys. The study includes a youth questionnaire for ages 10-15 and an adult survey for those 16 and over. For our study, we focus on the adult questionnaire.[11]

The study aims to provide high-quality data on health, work, education, income, family, and social life to understand the long-term effects of social and economic changes and policy interventions in the UK. It collects both objective and subjective indicators and supports research

[11] The Dataset also includes a General Population Sample, an Ethnic Minority Boost Sample, the former British Household Panel Survey sample, and an Immigrant and Ethnic Minority Boost Sample.

across multiple disciplines, including sociology, economics, geography, psychology, and health sciences.

We restrict the sample to individuals in paid employment between 20 and 59 years old that are single, including those that are divorced, widowed or not legally married to have a representation of individuals living on their own.[12]

Since we are mainly interested in taking individuals into their working age period, we remove from the sample those that declare themselves to be full-time students and those that are already retired. For the outcome variable, we take the Labor income, which is the sum of net pay from full-time job, self-employment, and second job. Labor income is one of the 6 components of the variable "Total estimated net monthly income", where "net" refers to net of taxes on earnings and national insurance contributions. However, considering that arguably some of the income components may not be related to effort, as they could originate from social benefits or unearned income variables we consider only labor income for the main analysis.[13]

From this variable, we first remove those incomes that are equal to zero, and then, to avoid as much as possible the presence of extremely high or low values that may be resulting from survey mistakes, the top 1% and bottom 1% percentiles of our income distribution, a procedure that leaves us with a final sample of 8197 observations.[14]

To reflect the fact that we are comparing subjects that are in different stages of their lives and to partially correct for life-cycle dynamics, we adjust our outcome variable for age. In particular, following Palomino *et al.* (2020); Brunori & Neidhöfer (2021); Brunori *et al.* (2023a), our age adjustment procedure is obtained by regressing the log of labor income on age and age squared, centered with respect to the median age of the sample, a well accepted procedure in the literature on intergenerational mobility (Haider & Solon, 2006; Almås & Mogstad, 2012; Salas-Rojo & Rodríguez, 2022) among many others).[15]

Hence, we run:

$$\log y_i = \beta_0 + \beta_1 \text{age\_centered}_i + \beta_2 \text{age\_centered}_i^2 + \varepsilon_i.$$

And we the take the sum of the constant and the residual as the age-adjusted outcome variable.

Multiple works related to the study of income variables in the equality of opportunity literature have opted for a logarithmic transformation or deviation with respect to the mean income. However, we here opt for income in its raw values, following those studies that have

[12]To build this variable, we rely on the definition of "legal marital status" provided by the dataset. With respect to the widowed, we however removed those individuals that earn income from "spouse previous employee", since arguably we believe those incomes do not come from their own effort.

[13]See appendix 3.5.2 for a full description of all income components.

[14]Such procedure is suggested by the dataset providers meta-file, which we recall for further clarifications.

[15]The literature suggests that centering with respect to the median age of a sample representing a working-age population allows for meaningful comparisons among individuals at different stages of their life cycle, using the peak of their predicted income as a reference point. In our sample, the median age is 36. By estimating a simple OLS model of the form:

$$\log Y = \beta_0 + \beta_1 \text{age} + \beta_2 \text{age}^2 + \varepsilon,$$

we confirm that the age at which maximum income is observed is approximately 40 years, a value close to the median age. For further details, we refer to subsection 3.5.3 of the Appendix.

implemented Adaptive Kernel approaches (Jenkins & Van Kerm, 2005; Jäntti *et al.*, 2015), and recalling specifically Charpentier & Flachaire (2015) and the seminal work by Hildenbrand *et al.* (1998), who argue the use of adaptive method on income in raw value is already almost equivalent to the use of a standard kernel on income transformed into its logarithmic form, hence suggesting no further transformation of the dataset.

Our outcome variable will then be:

$$\tilde{y}_i = \exp(\beta_0 + \varepsilon_i).$$

In the Appendix 3.5.4 we repeat the analysis measuring the point-steepness of the inverse CDFs for total net monthly income, hence including in our analysis the re-distributional effects from government policies.

Based on this outcome, we then divide the sample into types, creating a variable representing the circumstances an individual faces as non-responsibility characteristic.

As circumstances, we consider gender (coded as 1 if male and 0 if female), country of birth (1 if the individual was born in the UK and 0 otherwise, with all foreign-born aggregated into a single category), and parental occupation, measured as the highest occupational status between the two parents. The value of parental occupation is taken from National Statistics Socio-economic Classification (NS-SEC)[16] of parents' job when the respondent was aged 14, which we compress into a 5-categorical variable taking the value equal to 0 if the parent was unemployed when individuals were 14, 1 if low skilled, 2 if medium-low skilled, 3 if medium-high skilled, 4 if high skilled.

We then take the highest value among the two parents as a proxy for the parental occupation level. This procedure gives us 20 types, a number consistent with most of the literature (see for example Brunori *et al.* (2023b) for a recent discussion on the different methods to define types). The obtained types are described in table 3.1, while table 3.2 summarize our outcome variable, labor income, for each of the type.[17]

[16]The original variable is in 8 categories, which are: larger employer/higher professional, higher management, Lower management/professional, Intermediate, Small employers/own account, Lower supervisory /technical, Semi-routine and Routine. To this list, we also add the possibility that the parents were unemployed when individuals were 14 years old. In order to avoid confusion, we remove from the sample those who have one of the two parents deceased when 14 years old.

[17]With respect to this sample size, we recall type's numerousity may represent an issue, especially if the type does not reach an amount of at least 100 observations (see Brunori & Neidhöfer (2021) and Chapter 19 of Hansen (2022). However, we opt for a manual definition of types in the main analysis and we better address this issue in section 3.3.4

Type	Freq.	Percent	Description
1	28	0.34	Females, Non-Uk, No P.O.
2	105	1.28	Females, Non-Uk, Low Skilled P.O.
3	139	1.70	Females, Non-Uk, Medium-Low P.O.
4	219	2.67	Females, Non-Uk, Medium-High P.O.
5	138	1.68	Females, Non-Uk, High-Skilled P.O.
6	130	1.59	Females, Uk, No P.O.
7	1015	12.38	Females, Uk, Low Skilled P.O.
8	849	10.36	Females, Uk, Medium-Low P.O.
9	1399	17.07	Females, Uk, Medium-High P.O.
10	503	6.14	Females, Uk, High-Skilled P.O.
11	33	0.40	Males, Non-Uk, No P.O.
12	87	1.06	Males, Non-Uk, Low Skilled P.O.
13	142	1.73	Males, Non-Uk, Medium-Low P.O.
14	210	2.56	Males, Non-Uk, Medium-High P.O.
15	114	1.39	Males, Non-Uk, High-Skilled P.O.
16	98	1.20	Males, Uk, No P.O.
17	756	9.22	Males, Uk, Low Skilled P.O.
18	658	8.03	Males, Uk, Medium-Low P.O.
19	1111	13.55	Males, Uk, Medium-High P.O.
20	463	5.65	Males, Uk, High-Skilled P.O.
Total	8197	100.00	

Table 3.1: *Definition of types and respective number of observations. Source: Our elaboration from UK Understanding Society (2009–2011).*

Type	N	Mean	SD	Skew.	Kurt.	Min	p1	p25	p50	p75	p90	p99	Max
1	28	1152.28	707.37	0.63	2.43	205.09	205.09	637.61	1033.66	1572.04	2400.00	2600.00	2600.00
2	105	1163.61	637.38	1.00	3.76	226.24	240.21	705.39	1037.39	1525.29	2107.08	3143.41	3202.20
3	139	1219.11	637.76	0.94	3.45	255.65	281.95	750.32	1065.72	1547.73	2212.44	3075.99	3268.62
4	219	1372.71	736.53	0.78	3.14	184.76	197.36	843.12	1184.31	1838.70	2457.88	3377.84	3521.73
5	138	1477.88	719.07	0.24	2.51	182.36	213.72	961.53	1506.44	1965.08	2386.78	3115.50	3446.88
6	130	1055.86	644.44	1.43	5.49	225.80	255.62	562.05	982.80	1330.28	1845.69	3263.28	3521.73
7	1015	1106.05	582.46	1.05	4.59	178.87	213.02	659.05	1025.91	1407.61	1847.51	2920.71	4018.96
8	849	1155.30	620.52	1.15	4.80	173.65	256.20	703.53	1068.53	1444.87	1939.10	3284.46	3922.99
9	1399	1372.47	667.78	0.71	3.40	171.33	260.21	884.84	1288.12	1760.87	2314.62	3284.64	3937.52
10	503	1493.39	737.09	0.66	3.18	169.40	234.27	972.79	1389.71	1924.22	2518.73	3596.32	3920.71
11	33	1219.74	588.62	0.87	4.33	300.27	300.27	777.70	1154.68	1460.41	1767.49	3040.43	3040.43
12	87	1365.43	734.94	1.16	4.58	202.75	202.75	869.08	1279.00	1635.59	2500.00	4087.85	4087.85
13	142	1434.94	753.22	1.06	3.99	235.68	312.28	945.03	1290.47	1778.06	2545.83	3577.44	3939.62
14	210	1502.60	820.46	0.98	3.64	214.54	303.00	913.07	1307.69	1966.88	2778.93	3723.30	4553.01
15	114	1855.61	949.38	0.35	2.14	308.26	400.73	1034.06	1731.10	2554.61	3211.10	3758.60	4296.30
16	98	1316.92	618.88	0.51	2.91	275.81	275.81	911.82	1229.47	1689.14	2104.20	2930.66	2930.66
17	756	1474.48	654.72	0.93	4.33	168.30	270.29	1042.22	1349.54	1829.95	2373.29	3513.25	4193.95
18	658	1555.28	701.36	0.67	3.56	178.06	267.25	1085.96	1493.35	1934.30	2504.76	3537.81	4049.72
19	1111	1621.95	712.41	0.68	3.55	163.88	280.16	1153.21	1504.59	2019.98	2609.54	3634.63	4203.73
20	463	1807.33	788.71	0.43	3.03	170.43	248.90	1246.14	1763.87	2249.76	2918.59	3961.48	4129.23
Total	8197	1407.38	714.80	0.82	3.65	163.88	245.20	899.15	1301.05	1802.53	2373.32	3502.94	4553.01

Table 3.2: *Summary statistics of labor income by types. Labor income is adjusted by the age of the individuals. Source: Our elaboration from UK Understanding Society (2009–2011).*

3.3.2 Methodology: The Kernel density approach

Among the multiple techniques that have been implemented by the EOp literature to measure the impact of non-responsibility characteristics on outcomes, much of the debate has been revolving around the choice of parametric or non-parametric estimates.

Clearly, both estimates suffer from omitted variables biases, with unobserved circumstances or effort playing a role in individuals' outcomes. As pointed out in Ramos & Van de Gaer (2016, 2021), parametric methods, which rely on functional form assumptions, are more prone to specification errors. However, such a choice may be justified by considering that (1) first, multivariate regression frameworks use data more efficiently when controlling for circumstances and they can use inference tools for finite sample sizes. (2) Second, handling continuous variables (that could be circumstances) is more challenging with non-parametric techniques, which require large datasets for estimates' reliability and (3) parametric methods allow for estimating the partial effect of specific circumstances, enabling the calculation of inequality of opportunity due to those circumstances.

Nonetheless, we recall that non-parametric approaches handle individual observations more transparently, providing a more flexible way to capture the true effect of responsibility and non-responsibility characteristics on outcomes. Moreover, parametric approaches need a functional form to be imposed and a finite number of types to obtain identification of outcomes. We hence opt for non-parametric estimation, which directs us toward the challenge of identifying the most efficient and precise method for estimating the cumulative distribution function from observational data and constructing our opportunity sets.

Following O'Neill, D and Sweetman, O and Van de gaer, Dirk (2000), we apply a kernel density estimation technique to visualize the entire distribution of outcome conditional on the type and using a Gaussian Kernel Function. In the mentioned paper, the authors concentrated on estimating the distribution of children's income conditional on their father's income, applying this method to a continuous variable to focus on intergenerational mobility.

Different from their work, we instead condition individuals' outcomes to the discrete set of circumstances defined in subsection 3.3.1, representing a subset of all the possible non-responsibility variables as typically done in the Inequality of opportunity literature.

We choose to use a Gaussian kernel over other options, such as the Epanechnikov kernel, in line with Hansen (2022). In most practical contexts, these two kernels produce quite similar density estimates, with the Gaussian providing more smoothness. The Gaussian kernel is also often preferred for its convenience, as it generates a density estimator that has derivatives of all orders and remains non-zero for all (y), which is important as we need to compute the inverse of it.

The smoothing process is obtained following the Adaptive Kernel approach (Silverman (1986); Van Kerm (2003) and Van Kerm (2012) for an application using Stata), whose estimator adjusts the window width to be narrower where the density is high and wider where the density is low, thereby preserving detail in regions with abundant data and reducing noise in regions with sparse data. The smoothing process is a necessary step to compute the point-slope of the derived curve and avoid yielding undefined values that we would obtain at the steps of the curve by using empirical CDF.

The adaptive kernel density estimate is given by:

$$\hat{f}(y) = \frac{1}{\sum_{i=1}^{n} w_i} \sum_{i=1}^{n} \frac{w_i}{h_i} K\left(\frac{y - y_i}{h_i}\right)$$

where y_i represents the data points associated with their respective sample weights w_i, and K is the kernel function. The term $h_i = h \cdot \lambda_i$ is derived from a global bandwidth parameter h, while λ_i acts as a factor that enables adaptive bandwidth, making it proportional to the square root of the data density at each sample point (Portnoy & Koenker, 1989; Van Kerm, 2003). The use of varying (or local) bandwidths in kernel density estimation is widely recognized for its effectiveness in estimating long-tailed density functions. A fixed (or global) bandwidth can lead to undersmoothing in sparsely observed areas and oversmoothing in densely observed ones. By adjusting the bandwidth across the data's support, this method reduces estimate variance in sparse regions and bias in dense regions (Van Kerm, 2003, 2012).

Moreover, when the data concentration is markedly heterogeneous, using a fixed bandwidth for kernel density estimation often leads to oversmoothing in dense areas and undersmoothing in sparse areas. To address this, narrower bandwidths should be used in dense regions (the middle)

and wider ones in sparse regions (the tails).
The corresponding smoothed Kernel CDF is then obtained through the integration of the Probability Density Function above:

$$\hat{F}(y) = \int_{-\infty}^{y} f(y)\,dy = \frac{1}{\sum_{i=1}^{n} w_i} \sum_{i=1}^{n} w_i \cdot I\left(\frac{y - y_i}{h_i}\right)$$

We apply this method to our sample, resulting into a number of 20 estimated CDF of age-adjusted Labor income conditional on the type that we represent in Figure 3.2.

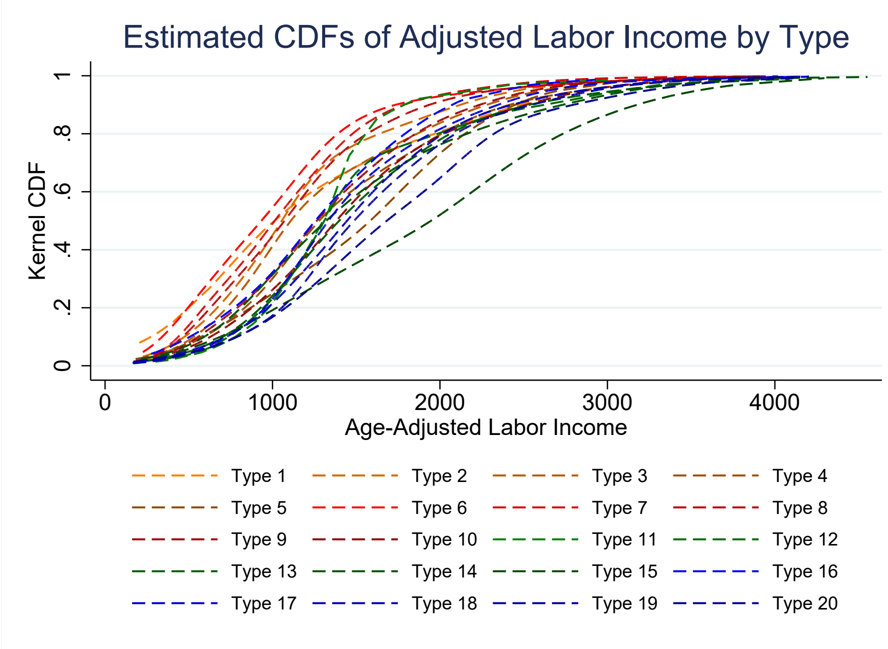


Figure 3.2: *Estimated CDFs by type through adaptive Kernel density approach. Source: our elaboration from UK understanding society(2009-2011).*

Notably, in Figure 3.2, we observe that some of the cumulative distribution curves either dominate or intersect others. To enhance clarity, we provide table 3.3 that summarizes these relationships: dominance relationships are highlighted in blue, where the subscript indicates which type dominates which; intersections are highlighted in red. From the table, we can see that types 19 and 20 have the highest opportunity sets, as their curves dominate most of the others. By contrast, types 1 to 5, representing non-UK females with different levels of parental occupation, exhibit the lowest opportunity sets. Their curves are either dominated or intersect with some of the others, but are never above. In the next section, we explore whether these (dis)advantages in the average reward-to-effort correspond to similar patterns in sensitivity to effort.

Type	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	–	C_1	C_1	C_1	C_1	C_1	C_1	C_1	C_1	D_{10-1}	C_1	C_2	D_{13-1}	D_{14-1}	D_{15-1}	C_1	C_1	C_1	D_{19-1}	D_{20-1}
2	:	–	D_{3-2}	D_{4-2}	D_{5-2}	D_{6-2}	C_1	C_3	D_{9-2}	D_{10-2}	C_1	D_{12-2}	D_{13-2}	D_{14-2}	D_{15-2}	C_2	D_{17-2}	D_{18-2}	D_{19-2}	D_{20-2}
3	:	:	–	C_1	C_2	D_{6-3}	D_{7-3}	D_{8-3}	C_1	D_{10-3}	C_1	D_{12-3}	D_{13-3}	D_{14-3}	D_{15-3}	C_2	C_2	D_{18-3}	D_{19-3}	D_{20-3}
4	:	:	:	–	C_3	D_{6-4}	D_{7-4}	D_{8-4}	C_1	C_2	C_1	C_2	D_{13-4}	C_6	D_{15-4}	D_{16-4}	C_1	C_2	D_{19-4}	D_{20-4}
5	:	:	:	:	–	D_{6-5}	D_{7-5}	D_{8-5}	C_1	C_2	C_1	C_2	C_2	C_2	D_{15-5}	D_{16-5}	C_1	C_2	C_2	D_{20-5}
6	:	:	:	:	:	–	C_1	C_1	D_{9-6}	D_{10-6}	C_1	D_{12-6}	D_{13-6}	D_{14-6}	D_{15-6}	D_{16-6}	D_{17-6}	D_{18-6}	D_{19-6}	D_{20-6}
7	:	:	:	:	:	:	–	D_{8-7}	D_{9-7}	D_{10-7}	C_3	D_{12-7}	D_{13-7}	D_{14-7}	D_{15-7}	C_1	D_{17-7}	D_{18-7}	D_{19-7}	D_{20-7}
8	:	:	:	:	:	:	:	–	D_{9-8}	D_{10-8}	C_1	D_{12-8}	D_{13-8}	D_{14-8}	D_{15-8}	C_1	D_{17-8}	D_{18-8}	D_{19-8}	D_{20-8}
9	:	:	:	:	:	:	:	:	–	D_{10-9}	C_1	C_1	D_{13-9}	C_5	D_{15-9}	C_2	D_{17-9}	D_{18-9}	D_{19-9}	D_{20-9}
10	:	:	:	:	:	:	:	:	:	–	C_1	C_2	C_2	C_1	D_{15-10}	D_{16-10}	C_1	C_1	D_{19-10}	D_{20-10}
11	:	:	:	:	:	:	:	:	:	:	–	C_1	C_1	C_1	C_1	C_1	C_1	C_1	C_1	C_1
12	:	:	:	:	:	:	:	:	:	:	:	–	C_4	C_1	C_1	C_2	C_8	C_2	C_2	C_1
13	:	:	:	:	:	:	:	:	:	:	:	:	–	C_1	C_1	D_{13-16}	C_1	C_6	C_3	D_{20-13}
14	:	:	:	:	:	:	:	:	:	:	:	:	:	–	D_{15-14}	D_{14-16}	C_1	C_1	C_1	D_{20-14}
15	:	:	:	:	:	:	:	:	:	:	:	:	:	:	–	D_{15-16}	C_1	C_1	C_1	C_3
16	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	–	D_{17-16}	D_{18-16}	D_{19-16}	D_{20-16}
17	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	–	C_3	D_{19-17}	D_{20-17}
18	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	–	D_{19-18}	D_{20-18}
19	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	–	C_5
20	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	:	–

Table 3.3: *Dominance and crossing relationship between types. Each cell above the diagonal compares type i (row) with type j (column).* D_{i-j} *= dominance of i on j;* C_x *= crossings. Analysis restricted to 5th to 95th percentiles. Source: Our elaboration from UK Understanding Society (2009–2011).*

3.3.3 Results

We compute both slopes and elasticities for all individuals belonging to the 20 type-specific inverse cumulative distribution functions (CDFs) of labor income.

Figure 3.3a presents the box plots of elasticity (left panel) and slope (right panel) for each type. For clarity, types are grouped into five categories: orange and red boxes represent non-UK females (orange) and UK females (red), respectively; green boxes correspond to non-UK males; blue boxes depict UK males. Darker colors indicate higher parental occupation. The ordering places types with higher opportunity sets to the right, consistent with Table 3.3.

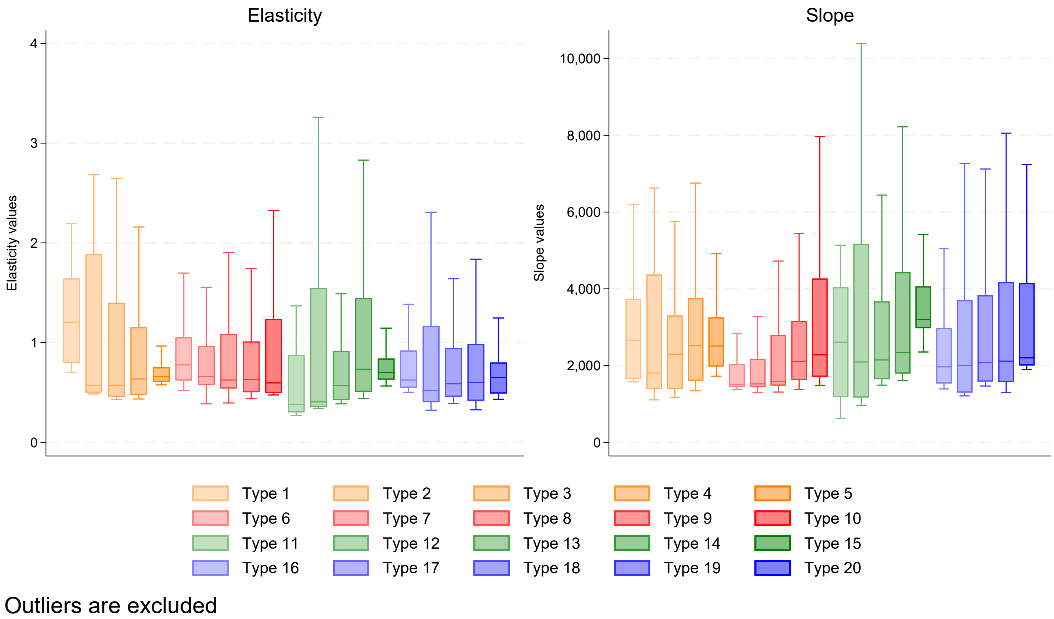
Some patterns can be observed. Elasticity tends to appear lower and more stable (with narrower interquartile ranges) as we move toward higher opportunity sets, showing similar medians and shorter whiskers. By contrast, individuals with medium-high and medium-low parental occupation sometimes display greater dispersion, reflected in longer whiskers. The slope boxplots, instead, seem to indicate higher values toward the right, with higher opportunity sets associated with slightly higher central tendencies. Moreover, the shorter variability observed among types with higher parental occupation appears consistent with the pattern already noted for elasticity.

We then assess how the measure varies across different levels of effort. To illustrate the overall distribution of the two metrics, we plot them against an aggregate measure of effort across types, removing the top and bottom 5 percentiles to obtain a clearer representation. The aggregate effort distribution is constructed by aggregating all estimated type-specific CDF values (ranging from 0 to 1) and dividing them into percentiles, so to have an aggregate effort measure.

Figure 3.3b presents boxplots of slope and elasticity across percentiles of this aggregate effort distribution. Both indicators display very similar patterns, generally increasing with effort. Elasticity tends to rise and exhibit greater variability as effort increases, with values higher than 1 around the 80th percentile. Simultaneously, the slope follows a similar trend with some deviations at the lower percentiles. These differences are due to our estimation method, which adjusts for the different measurement scales of income and effort, and they suggest that elasticity may be a more suitable indicator of sensitivity to effort.

Moreover, given also the near-perfect positive correlation between the two measures (Table 3.4), they can arguably be considered interchangeable. For this reason, we present the main results in terms of elasticity, while results based on the slope are reported in subsection 3.5.5 of the appendix for completeness.

(a) ***Panel A: Boxplots of Elasticities and Slopes by Type***



(b) ***Panel B: Elasticities and Slopes Distribution***

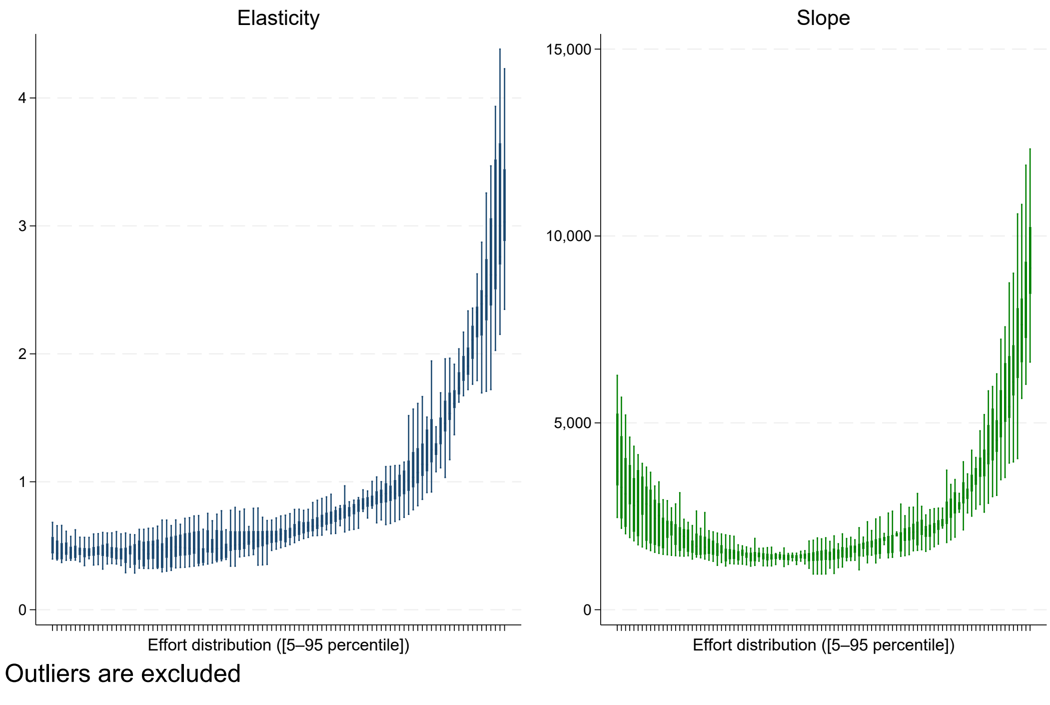


Figure 3.3: *Boxplots of elasticity and slope by types (Panel A) and elasticity–slope distribution across effort (Panel B). Source: our elaboration from UK Understanding Society (2009–2011).*

Table 3.4: *Pairwise correlation coefficients between* `elasticity` *and* `slope`

	Slope
Elasticity	0.9773***

Note: Source: our elaboration from UK Understanding Society (2009–2011). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We report the values obtained for the elasticity measure for each type in Table 3.5, which provides summary statistics by type. Some clear patterns emerge: mean elasticity decreases as the level of parental occupation increases (i.e., moving from types 1–5 to 6–10, 11–15, and 16–20), while maximum values tend to rise with parental occupation.

Two caveats are worth noting. First, the presence of extremely high values skews the distribution, widening the gap between mean and median. Second, types with fewer observations tend to display higher means. These features suggest that the mean may overstate differences across types. In this context, the median may therefore provide a more informative and robust basis for comparing elasticities across types.

Table 3.5: *Summary statistics of elasticity by types*

Type	N	Mean	SD	Skewness	Kurtosis	Min	p01	p25	p50	p75	p90	p99	Max
1	28	1.260927	0.4981495	0.45745	1.914771	0.7005736	0.7005736	0.7975436	1.205214	1.644886	2.036727	2.194269	2.194269
2	105	1.339124	2.030682	4.591822	25.56494	0.4846759	0.4846871	0.4974155	0.5719981	1.891033	2.250126	12.81384	13.33979
3	139	1.111513	1.406265	4.942256	32.30056	0.4308355	0.4308355	0.4564340	0.5723417	1.400154	1.931707	8.755197	11.64079
4	219	1.156085	1.378894	3.709021	18.97455	0.4345865	0.4345996	0.4757964	0.6351906	1.154716	2.451055	7.475068	9.676678
5	138	1.034154	1.467817	5.710778	39.97331	0.5763079	0.5763224	0.6070111	0.6599437	0.7531046	1.283912	7.064962	13.10761
6	130	1.698349	2.700286	3.574986	16.84364	0.5218233	0.5222979	0.6200029	0.7765524	1.052748	4.389936	13.89280	17.48364
7	1015	1.592353	4.554071	12.89889	229.6196	0.3863255	0.3865772	0.5734885	0.6592616	0.9650979	2.803976	16.90292	98.36217
8	849	1.398545	2.519564	6.267150	62.69545	0.3948226	0.3950544	0.5401699	0.6247384	1.088301	2.436198	13.16032	37.39091
9	1399	1.295212	2.661312	10.30611	154.2789	0.4404832	0.4407749	0.5014144	0.6290692	1.011038	2.254235	11.63356	51.76796
10	**503**	**1.232115**	**1.966223**	**6.434239**	**53.59330**	**0.4749236**	**0.4752843**	**0.4921991**	**0.5965816**	**1.238335**	**2.157765**	**12.18268**	**21.63495**
11	33	1.569684	3.915018	4.101642	19.27514	0.2682316	0.2682316	0.3010063	0.3801103	0.8779539	1.792584	20.63817	20.63817
12	87	1.129890	1.663448	4.923977	34.64951	0.3398495	0.3398495	0.3547717	0.4057930	1.546663	2.726524	13.31194	13.31194
13	142	1.118719	1.563294	3.576707	17.24471	0.3864496	0.3871840	0.4232689	0.5704577	0.9165999	2.872536	7.431758	10.81664
14	**210**	**1.422852**	**3.465212**	**9.846825**	**109.6203**	**0.4396121**	**0.4396422**	**0.5066466**	**0.7326496**	**1.448038**	**2.416400**	**9.290298**	**42.90973**
15	114	0.997717	1.031591	6.118287	49.79240	0.5650813	0.5651702	0.6286345	0.7004729	0.8404211	1.707864	3.634747	9.864629
16	98	1.243717	1.831037	3.341468	12.88358	0.5021693	0.5021693	0.5476658	0.6246491	0.9205220	1.696536	9.546462	9.546462
17	756	1.325155	3.234236	7.649161	71.51700	0.3222216	0.3222833	0.4013623	0.5182284	1.167769	1.918005	17.34310	40.05689
18	658	1.216498	2.120942	6.709937	64.11853	0.3892632	0.3895061	0.4574831	0.5870998	0.9472457	2.651891	10.07435	28.35199
19	1111	1.196335	2.196365	7.646213	86.02341	0.3257644	0.3259240	0.4173903	0.5988980	0.9852737	2.425499	10.17396	33.89511
20	**463**	**1.131600**	**1.575304**	**5.048609**	**35.10720**	**0.4319459**	**0.4319854**	**0.4896479**	**0.6508976**	**0.8009440**	**2.620371**	**10.28514**	**14.18353**
Total	8197	1.303058	2.754545	12.19740	270.5618	0.2682316	0.3262029	0.4861102	0.6305915	1.039749	2.343655	12.18268	98.36217

Note: Descriptive statistics for the variable *elasticity*, by type. Reported statistics include the number of observations (N), mean, standard deviation (SD), skewness, kurtosis, minimum, and selected percentiles (p01, p25, p50, p75, p90, p99, and maximum). The last row provides the corresponding summary statistics computed over the full distribution. Source: our elaboration from UK Understanding Society (2009-2011).

To illustrate in greater detail some patterns in the elasticity measure, we provide a graphical analysis for three selected types, namely type 10, 14, and 20, highlighted in bold in Table 3.5.

These types were chosen to capture variation across gender, country of origin, and parental occupation. In the section 3.5.5 of the appendix, we also replicate the analysis with respect to the three most numerous types of our sample.

Specifically:

- **Type 10**: Female, UK-born, with high-skilled parental occupation.
- **Type 14**: Male, non-UK-born, with medium-high parental occupation.
- **Type 20**: Male, UK-born, with high-skilled parental occupation.

These type-profiles allow us to compare elasticity distributions across gender and country of birth, while keeping parental occupation at relatively high levels.

The left panel of Figure 3.4 shows the probability and cumulative distribution functions (PDFs and CDFs) for the three selected types. Then, to better explore the relationship between sensitivity and reward to effort, the right panel illustrates their relative opportunity sets, expressed as deviations from the sample average of labor income.

In this respect, we observe that Type 20 exhibits a higher average reward to effort, as indicated by the blue line consistently dominating the other two curves. Moreover, in terms of steepness, the blue line reaches the sample average labor income at lower effort levels. In contrast, since the lines corresponding to Types 10 and 14 intersect, we cannot clearly determine which of the two has a stronger advantage across the effort distribution, as the two intersect around the average values.

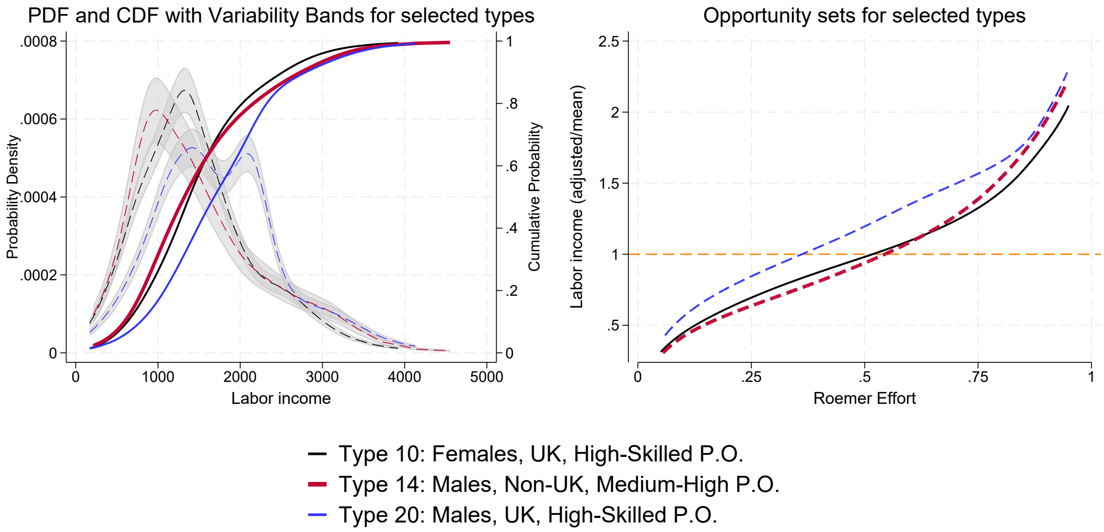


Figure 3.4: *Kernel densities and opportunity sets for age-adjusted labor income, shown for three selected types: UK females with high-skilled parental occupation (Type 10, black line), Non-UK males with medium-high parental occupation (Type 14, Red line), and UK males with high-skilled parental occupation (Type 20, Blue line). The left panel presents type-specific kernel density estimates and cumulative distribution functions, along with variability bands (grey). The x-axis represents age-adjusted labor income. The right panel plots Roemerian effort on the x-axis and the deviation of labor income from the sample-average on the y-axis. For clarity, the top and bottom 5 percentiles of the Roemer's effort distribution are excluded. Source: Our estimation based on UK Understanding Society (2009–2011).*

When examining sensitivity to effort, we observe some notable differences, as shown in Figure 3.5. These differences appear particularly evident when considering percentiles of the Roemerian effort distribution.

Specifically, Type 14 (red line) seems to display greater sensitivity to effort at higher effort levels, suggesting that responsiveness to effort may be more pronounced for this group in the upper tail of the distribution. In contrast, Type 20 (blue line), which was associated with higher average labor income (see Table 3.2), appears to maintain relatively stable elasticity across all effort levels, indicating a more uniform reward structure.

The female group (Type 10, black line) generally shows lower elasticity values compared to Type 14, which may reflect a lower responsiveness of labor income to effort throughout the distribution.

Overall, all three types tend to exhibit low elasticity values (below 1) at lower levels of Roemer effort. Conversely, the measure exceeds 1 for all types around the 75th percentile, which may suggest that higher rewards occur primarily in the upper part of the distribution.

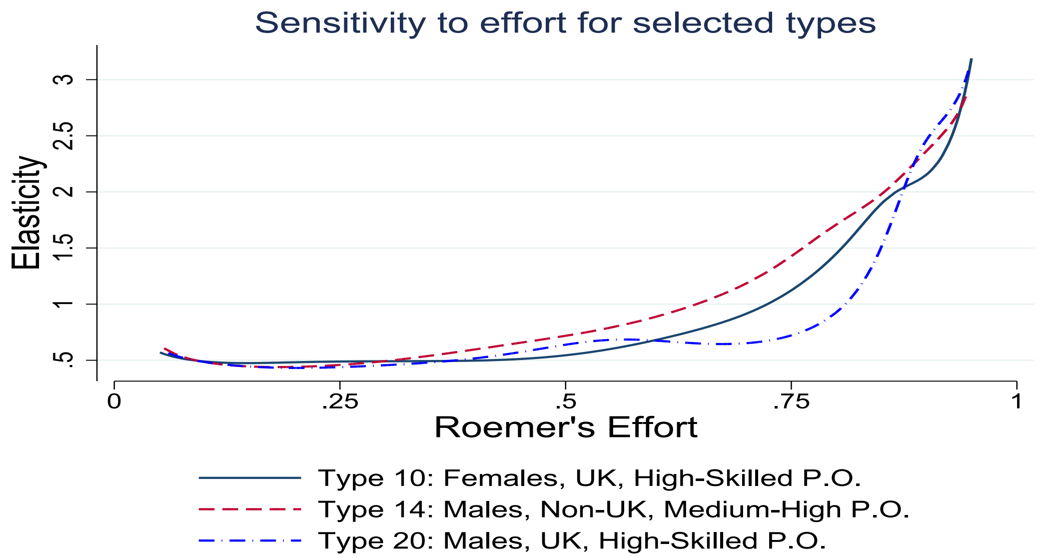


Figure 3.5: *Elasticity of age-adjusted labor income across the effort distribution, shown for three selected types: UK females with high-skilled parental occupation (Type 10, black line), Non-UK males with medium-high parental occupation (Type 14, red line), and UK males with high-skilled parental occupation (Type 20, blue line). The figure presents the elasticity values across the Roemer's effort distribution. For clarity, the top and bottom 5 percentiles of the effort distribution are excluded from the graph. Source: Our estimation based on UK Understanding Society (2009–2011).*

Pairwise comparisons

The results discussed in the subsection above reveal some interesting patterns concerning the differences between the average reward to effort (i.e., average income by type) and the sensitivity to effort experienced in each group. Moreover, higher levels of effort appear to be consistently associated with greater sensitivity, whereas the opposite trend is observed for all three types under analysis.

We now take a step further in the exploration of elasticity values by comparing specific pairs of types. In particular, we aim to isolate the effect of a single characteristic at a time, gender, parental occupation, or country of birth, holding the other two constant. This approach arguably allows for the most robust and meaningful comparisons possible between individuals.

First, we can confirm some of the previously reported results: a higher reward to effort does not necessarily translate into greater sensitivity to effort throughout all the distribution.

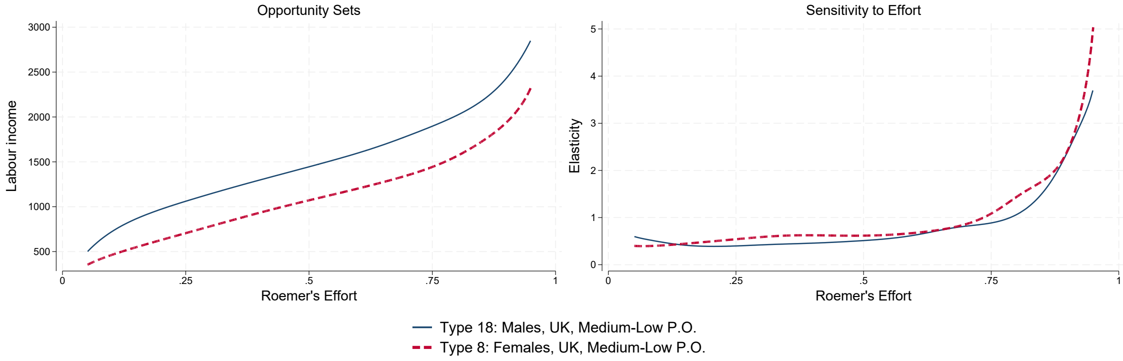
As shown in Figure 3.6a, Type 18 (Males, UK, Medium-Low Parental Occupation) consistently attains higher income levels for the same values of effort compared to its female counterpart. However, when examining sensitivity to effort, the two curves appear nearly identical across the entire distribution, which prevents drawing strong conclusions.

A similar pattern emerges when comparing different levels of parental occupation, as shown in Figure 3.6b. In this case, non-UK females with higher parental occupation levels (Type 5) attain higher rewards to effort compared to those with lower levels (Type 2). However, this does not clearly translate into greater sensitivity to effort, as Type 5 shows higher responsiveness only in the lower part of the distribution. By contrast, females with low parental occupation display higher sensitivity at higher effort levels. This raises the possibility that the advantage of greater sensitivity may depend on the specific segment of the effort distribution considered, rather than being uniform across the entire range.

Finally, when comparing the country of birth of males with high levels of parental occupation in Figure 3.6c, we observe a slightly greater, but not dominant, sensitivity to effort up to the highest percentiles of the distribution, among non-UK individuals. However, since the curves intersect several times, we cannot claim any robust pattern.

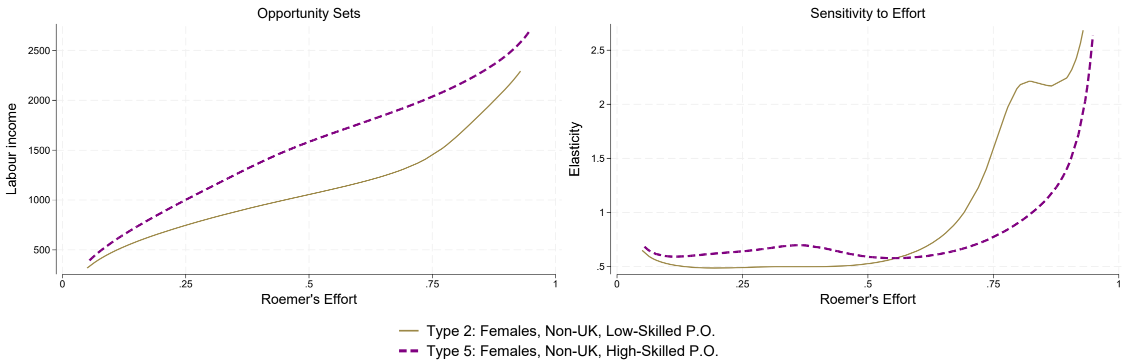
Pairwise Comparisons of Opportunity Sets and Elasticity

(a) Gender comparison



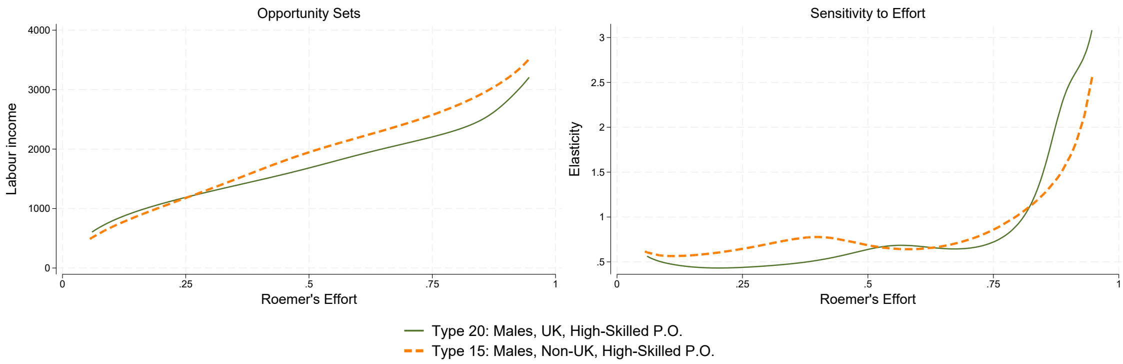
(a) *Males (Type 18) vs Females (Type 8), both UK, Medium-Low P.O.*

(b) Parental occupation



(b) *Females, Non-UK: Low-Skilled P.O. (Type 2) vs High-Skilled P.O. (Type 5).*

(c) UK vs Non-UK



(c) *Males, High-Skilled P.O.: UK (Type 20) vs Non-UK (Type 15).*

Figure 3.6: *Pairwise comparisons of opportunity sets and elasticities across three circumstances, holding constant the other two: (a) Gender comparison, (b) UK vs Non-UK comparison, and (c) Parental Occupation comparison. Source: our elaboration from UK Understanding Society (2009-2011).*

These results suggest that sensitivity to effort, namely the extent to which individuals can improve their outcomes by increasing effort, may represent an additional dimension of inequality of opportunity. This dimension does not always match the observed rewards to effort, since one does not necessarily imply the other. Our evidence also indicates that the measure depends on the position in the distribution: lower effort levels are usually linked to low elasticity, while higher effort levels are often linked to greater elasticity.

As these findings may still be influenced by methodological choices and sample biases, we recommend caution in interpreting the results.

In particular, the estimated elasticities depend on the choice of outcome variable, the composition of the sample, the definition of types, and the method used to estimate the probability density functions (PDFs), all of which could affect the results obtained.

We try to address some of these issues in the following pages. Specifically, in section 3.3.4 we conduct a set of robustness checks. First, we try to assess the statistical precision of our estimates by estimating confidence intervals. Second, we explore the sensitivity of our results to the definition of types by applying an alternative partitioning approach based on a machine learning technique. Finally, to check the extent to which our conclusions depend on the chosen outcome variable, we repeat the analysis using total net monthly income, results of which are reported, as already mentioned, in subsection 3.5.4 of the Appendix.

3.3.4 Robustness

Confidence Intervals

As elasticities and slopes are derived from a kernel density smoothing process, they are inherently subject to variability introduced by the estimation procedure. Specifically, their standard errors depend on the precision with which the density function $f(y)$ and its CDF $F(y)$ are estimated, since both are smoothed representations of the observed data. Because the accuracy of these kernel estimates directly affects the variability of the derived elasticity and slope measures, assessing their variance represents an important first step in evaluating the reliability of the results.

In principle, if the analysis were limited to the slope, defined as $1/f(y)$, the variability bands proposed by Van Kerm (2003, 2012) and shown in the graphical analysis of both the PDFs and CDFs in Figure 3.4, would provide a good approximation of confidence intervals for the estimated measures.[18]

However, since the elasticity depends on both the estimated density $f(y)$ and the cumulative distribution $F(y)$, and given that the estimation errors of these two functions propagate differently through the elasticity formula, their combined uncertainty may follow a complex pattern that is not easily captured by standard asymptotic approximations (Chen, 2017).

[18]However, these bands do not really correct for the asymptotic bias of kernel estimators, whose magnitude depends on the chosen bandwidth and on the shape of the underlying true distribution. For a fixed bandwidth, this bias remains even as the sample size increases. For this reason, several authors, including Bowman & Azzalini (1997), prefer the term “variability bands” rather than “confidence bands,” to emphasize that they reflect the sampling variability of the kernel estimate but not its bias correction. To address these issues, more robust confidence intervals for kernel density estimates can be obtained through either *plug-in* or *bootstrap* methods (Chen, 2017).

To address this issue, a nonparametric bootstrap with 500 replications is implemented. In each replication, individuals are resampled with replacement within their respective type, so that the relative size of each type remains unchanged. For every resample, both the density function $f(y)$ and the cumulative distribution $F(y)$ are re-estimated using the same kernel and bandwidth settings applied in the original estimation. The corresponding slope and elasticity values are then recalculated for each bootstrap draw, and the empirical distribution of these replicated estimates is used to construct percentile-based confidence intervals for the final elasticity measures.

Figure 3.7 presents the estimated confidence intervals for the elasticity and the slope across the overall effort distribution, with Panel A displaying the elasticity and Panel B the slope.[19] The confidence intervals tend to get larger toward the tails of the distribution, suggesting higher uncertainty in those regions, while they remain relatively narrow in the central part, indicating more stable estimates.

To provide further detail, Figure 3.8 reports the estimated bootstrapped confidence intervals for elasticity by each of the 20 type of our main analysis. The corresponding graph for the slope is shown in the appendix (figure 3.16). Two main factors seem to explain the width of the intervals. First, uncertainty increases with effort, as higher adjusted labor effort corresponds to sparser data in the upper range of the distribution. Second, types with fewer observations (such as type 1,11 and 12) display wider and less stable intervals, while those with larger sample sizes show more precise estimates. Hence, as partly expected, this pattern seems to suggest that inference is more reliable for those types with larger sample sizes, particularly in the lower and central parts of the effort distribution.

Panel A: Average Elasticity with 90% CI ***Panel B: Estimated Slope with 90% CI***

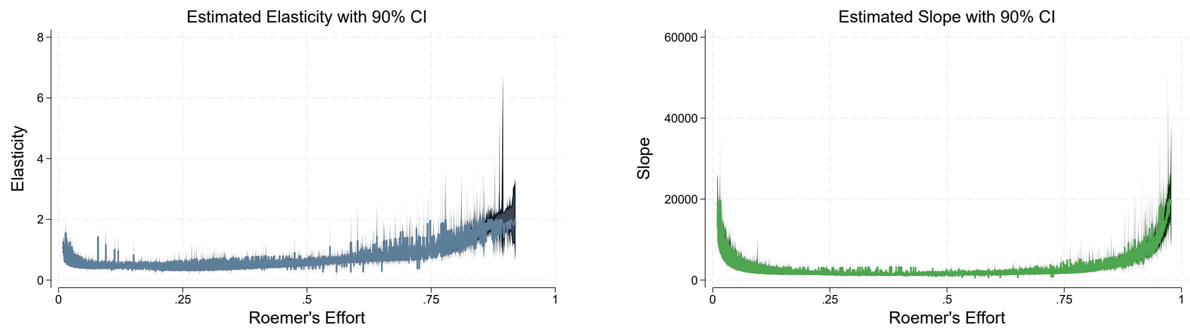


Figure 3.7: *Estimated elasticity (Panel A) and slope (Panel B) with 90% confidence intervals. Source: Author's elaboration from UK Understanding Society (2009–2011).*

[19]In the graphs, the display is restricted to effort values below 0.95 to exclude extreme observations in the upper tail, where the density is very low.

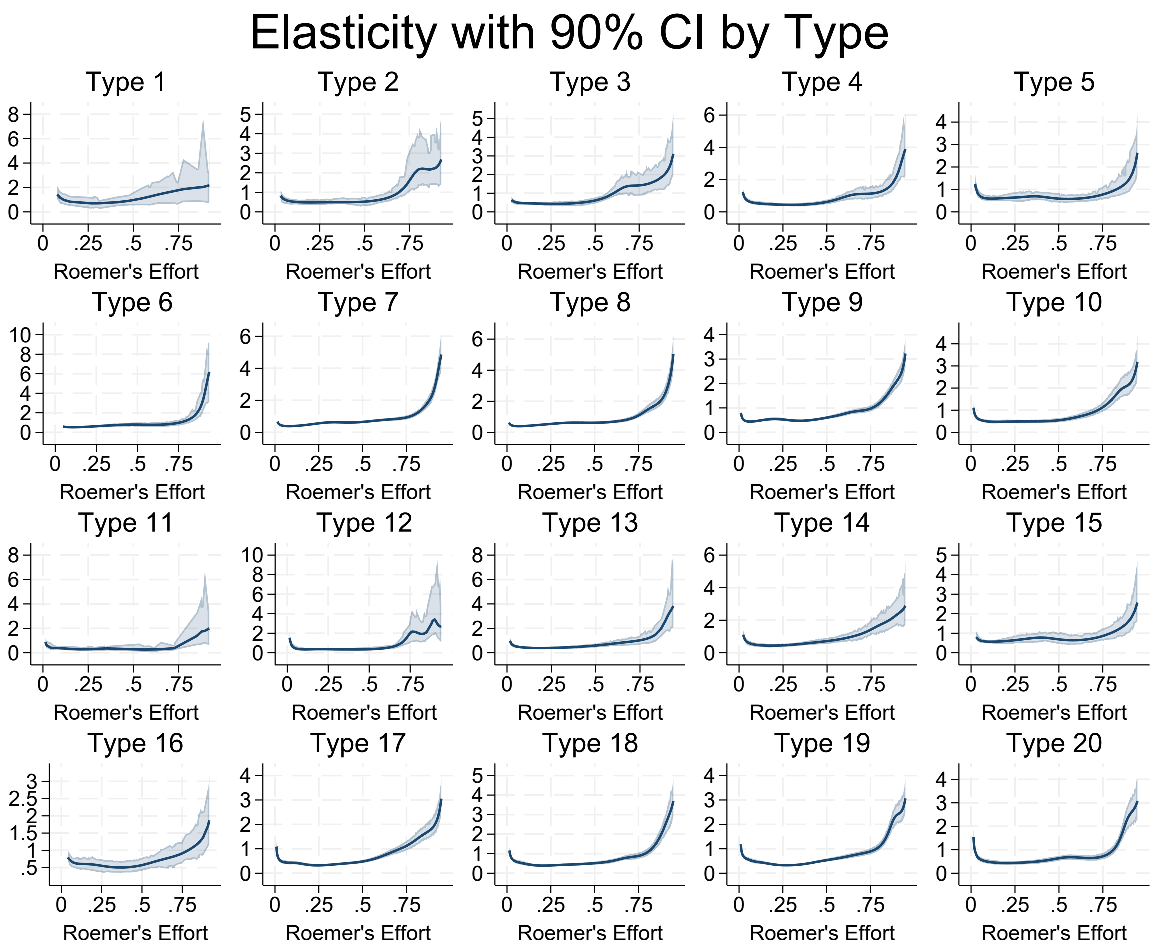
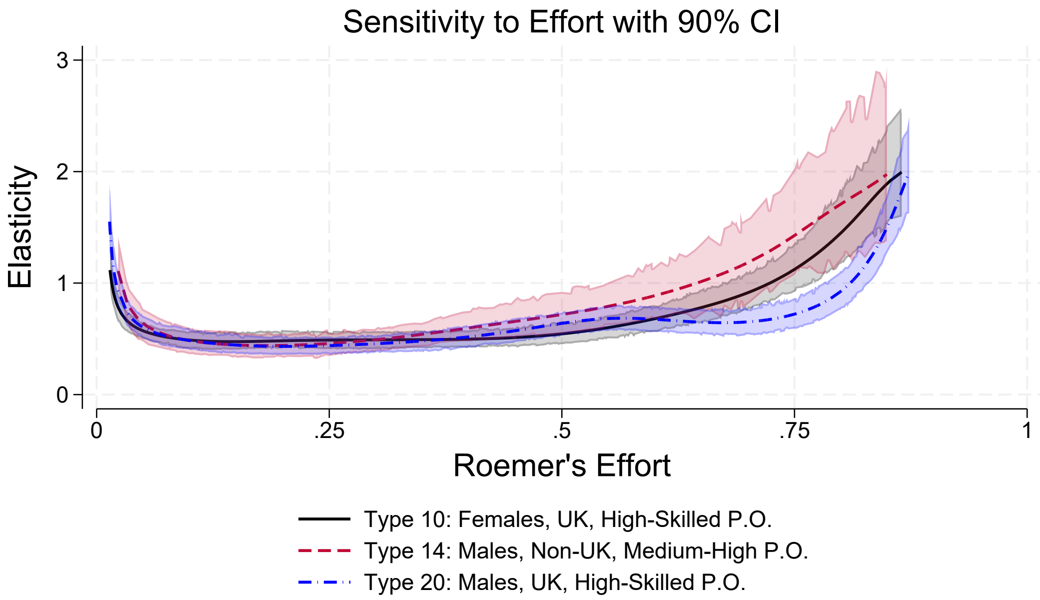


Figure 3.8: *Elasticity with 90% confidence intervals by type (20 panels). Source: Author's elaboration from UK Understanding Society (2009–2011).*

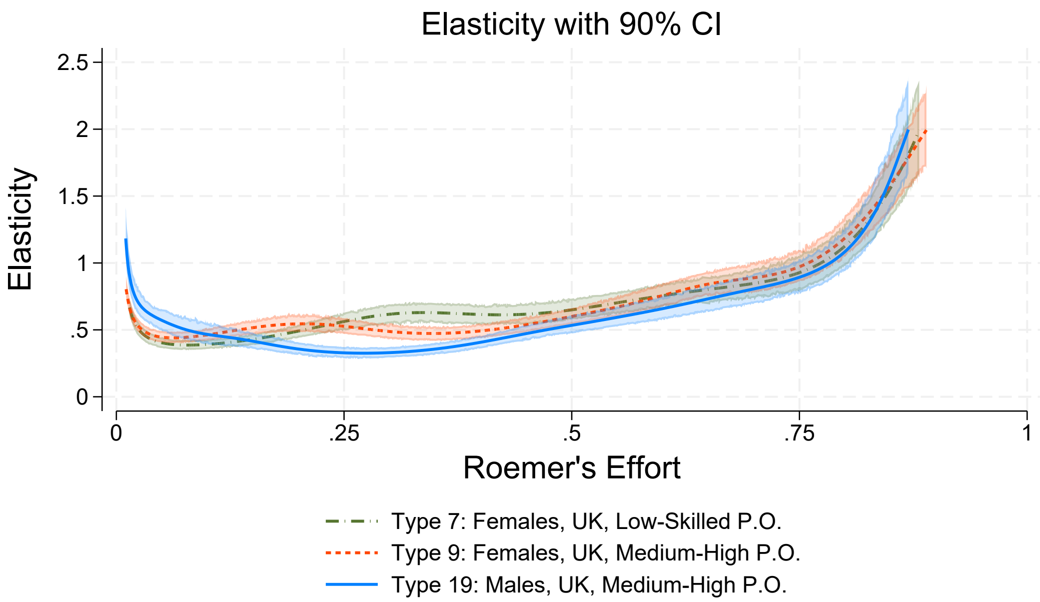
We then focus in greater detail on the estimated elasticity levels for the three types discussed in Section 3.3.3, while the corresponding results based on the slope are reported in Appendix 3.17. As shown in Figure 3.9a, the estimated confidence intervals of the elasticity measures tend to overlap in the central part of the effort distribution, which limits the possibility of drawing robust comparisons across groups in terms of dominance. However, some general patterns appear robust, such as elasticity values with values lower than 1 before the median of the effort distribution. This suggests that in the lower and central parts of the distribution, increases in effort are associated with less than proportional changes in adjusted labor income, suggesting lower sensitivity of income to effort among these individuals. In contrast, at higher effort levels, the elasticity tends to exceed one, except for Type 20, which displays a more stable pattern around an effort level of 0.8.

As the results based on type comparisons may be affected by differences in sample size across groups, we also examine the three most numerous types in our sample to assess the robustness of the previous findings (Figure 3.9b). In this case, the opposite tendency seems to hold: the estimated confidence intervals tend to overlap at higher effort levels, whereas some differences between types appears in the lower part of the distribution. At very low effort levels, males tend to display higher elasticity values, followed by a more stable pattern around the first quartile.

Around an effort level of approximately 0.4, Type 7 shows comparatively higher elasticity values, indicating a stronger variation of income at variation of effort in that range.



(a) *Elasticity for Types 10, 14, and 20*



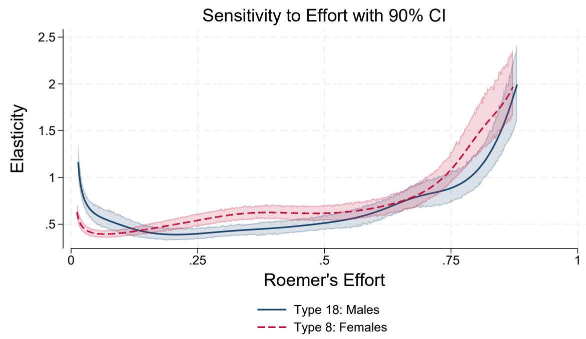
(b) *Elasticity for Types 7, 9, and 19*

Figure 3.9: *Elasticity with 90% confidence intervals for different type groups. Panel **A** refers to Types 10, 14, and 20, while Panel **B** refers to Types 7, 9, and 19. Source: Author's elaboration from UK Understanding Society (2009–2011).*

Finally, Figure 3.10 replicates the pairwise comparisons discussed in Section 3.3.3. Specifically, as shown in Figure 3.10a, the gender comparison suggests higher values of elasticity for men in the lower part of the effort distribution, with a reversal around the median, where women exhibit a greater sensitivity of income to effort. No robust differences can be identified in Figures 3.10b and 3.10c, as the confidence intervals of the corresponding elasticity estimates largely overlap across the entire range of effort.

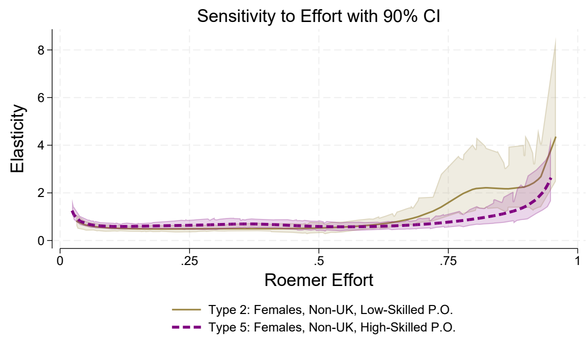
Pairwise Comparisons of Elasticity with 90% CI

(a) Gender comparison



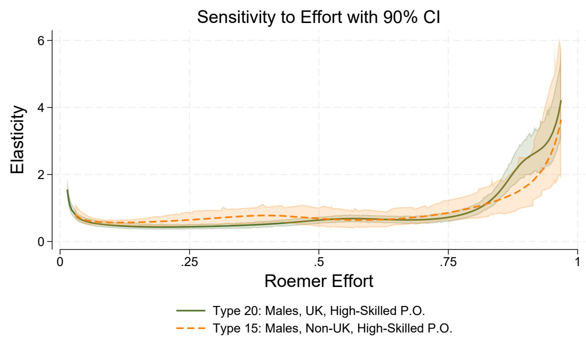
(a) *Males (Type 18) vs Females (Type 8), both UK, Medium-Low P.O.*

(b) Parental occupation



(b) *Females, Non-UK: Low-Skilled P.O. (Type 2) vs High-Skilled P.O. (Type 5).*

(c) UK vs Non-UK



(c) *Males, High-Skilled P.O.: UK (Type 20) vs Non-UK (Type 15).*

Figure 3.10: *Elasticity with 90% confidence intervals for three pairwise comparisons: (a) Gender, (b) Parental Occupation, (c) UK vs Non-UK.*

As these results may be influenced by the way types are defined and by their composition, future research could extend this analysis to include data-driven types, for instance, through machine-learning partitioning methods, in order to obtain more homogeneous and comparable groups. An illustration of one of these methods is provided in the following paragraph.

Types Partition: a Machine Learning Approach

The definition and partition into types provided in Section 3.3.1 leaves open considerations, mainly related to which, among all the possible divisions into subgroups, can be considered *optimal*. This is a typical issue in the literature on Equality of Opportunity (Brunori *et al.*, 2019), as the choice behind the circumstances to include and the resulting types obviously has an arbitrary component that can introduce both a downward or upward bias. The downward bias arises from the omission of unobserved circumstances, while the upward bias stems from overfitting due to an excessively fine partitioning (i.e., subdividing types into subtypes and creating cells with too few observations to support meaningful inference). Consequently, addressing the trade-off between upward and downward bias and determining the optimal type partition has recently led to various implementations, most of which rely on a data-driven approach to compute the extent to which circumstances can *predict* income, as summarized in the work of Brunori *et al.* (2023a,b).

Building on these works, we therefore implement a machine learning approach, partitioning our sample into types based on our selected circumstances (that is, gender, highest level of parental occupation, and ethnicity) using transformation trees (TrT). This approach,recently introduced by Hothorn & Zeileis (2021), improves robustness by reducing the arbitrariness of subgroup classification and allows us to partially validate our results with a more statistically robust approach to type partitioning.

Specifically, this method relies on a local likelihood maximization approach that segments the sample into distinct subgroups, with the division based on the most significant differences in the group-conditional distributions of outcomes. Consequently, it has been employed to estimate inequality of opportunity using an ex-post approach (i.e. after effort has been exerted) allowing us to visualize the entire income distribution conditioned on the types, which makes it particularly well-suited to our analysis. Referring to Brunori *et al.* (2023a) for a more detailed discussion, we must make three key choices when applying this method: (i) setting a confidence level to define the statistical differences that generate the split into different subgroups, which we set at $\alpha = 0.01$, (ii) selecting a polynomial order for the likelihood estimation, which we set of order 8. and (iii) defining the minimum number of observations required for each type, which we constrain to a minimum of 100 observations per cell in order to have a consistent number of individuals in each of the groups to compute meaningful inferences.[20]

We apply this method to our sample, determining the optimal number of subgroups and their

[20]However, we test whether any differences arise when modifying the three conditions above, finding no changes in the optimal partition selected by the algorithm and further supporting the robustness of our results.

respective composition based on age-adjusted labor income. Figure 3.11 shows how the method works in concrete. The algorithm divides the sample into 33 "nodes", each one of these resulting from the statistical relevance of the circumstances in predicting the income variable and leading to an optimal number of 17 types (the final nodes). Each one of these types has a population sample represented by the number in the graph and Empirical CDFs that are different from one another[21].

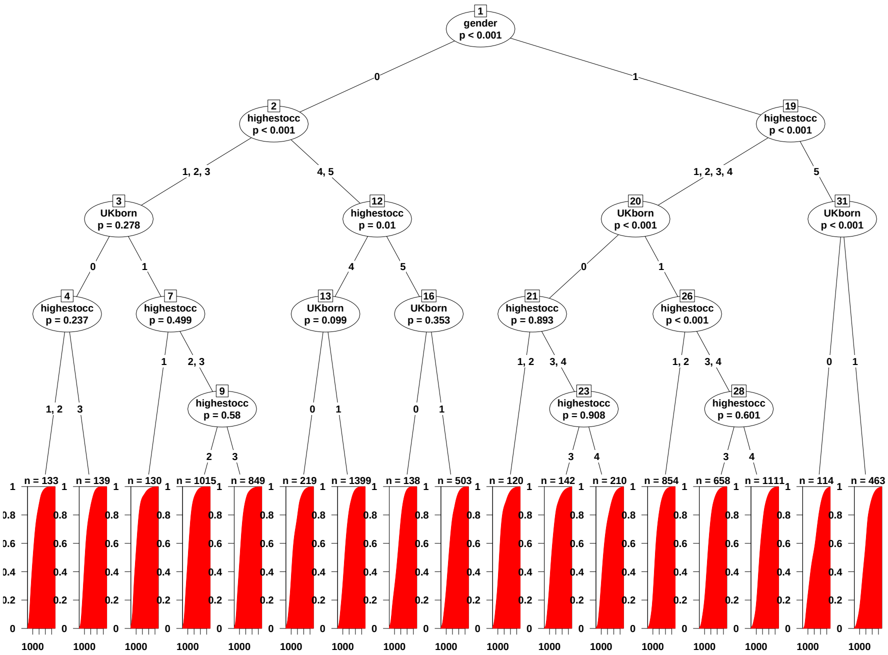


Figure 3.11: *Type partioning obtained through ML techinque. Source: our elaboration from UK Understanding Society (2009-2011).*

The type partition obtained through machine learning is described in table 3.6, which point out the new composition of types and the number of observation within each of the new sub-groups. To provide comparisons with the type used in our main analysis ("Manual types"), we show how these are in fact aggregated by the algorithm in order to compute the newest optimal partition. With respect to that, we notice how the circumstances related to low or no parental occupation level are aggregated in order to create a sub-group for type 1, 10 and 13, which is what reduces the final number of types to 17. Another difference emerges in the type ranking, which is now provided by the algorithm (contrary to Table 3.2) and indicates which groups have higher opportunity sets relative to the others with increasing number. This is more clearly illustrated in Table 3.7, which provides descriptive statistics of labor income under the new type partitioning and suggests that Type 17 (former Type 20) and Type 16 (former Type 15) tend to dominate the other curves across all percentiles of the labor income distribution.

[21]we emphasize that we do not account for the possibility of expanding our dataset by incorporating additional circumstances beyond the three mentioned, which would surely alter our results.

ML Type	**Manual Types**	**Freq.**	**Percent**	**Description**
1	[1] + [2]	133	1.62	Females, Non-UK, low or no P.O.
2	[3]	139	1.70	Females, Non-UK, medium-low skilled P.O.
3	[6]	130	1.59	Females, UK, no P.O.
4	[7]	1015	12.38	Females, UK, low skilled P.O.
5	[8]	849	10.36	Females, UK, medium-low skilled P.O.
6	[4]	219	2.67	Females, Non-UK, medium-high P.O.
7	[9]	1399	17.07	Females, UK, medium-high P.O.
8	[5]	138	1.68	Females, Non-UK, high skilled P.O.
9	[10]	503	6.14	Females, UK, high skilled P.O.
10	[11] + [12]	120	1.46	Males, Non-UK, low or no P.O.
11	[13]	142	1.73	Males, Non-UK, medium-low P.O.
12	[14]	210	2.56	Males, Non-UK, medium-high P.O.
13	[16] + [17]	854	10.42	Males, UK, low or no P.O.
14	[18]	658	8.03	Males, UK , medium-low P.O.
15	[19]	1111	13.55	Males, UK, medium-high P.O.
16	[15]	114	1.39	Males, Non-UK, high P.O.
17	[20]	463	5.65	Males, UK, high P.O.
Total	—	8197	100.00	

Table 3.6: *Distribution of types by machine learning groups. Source: Our elaboration from UK Understanding Society (2009–2011).*

ML Type	N	Mean	SD	Skew.	Kurt.	Min	p1	p25	p50	p75	p90	p99	Max
1	133	1161.23	649.96	0.90	3.42	205.09	226.24	660.59	1037.39	1525.29	2114.62	3143.41	3202.20
2	139	1219.11	637.76	0.94	3.45	255.65	281.95	750.32	1065.72	1547.73	2212.44	3075.99	3268.62
3	130	1055.86	644.44	1.43	5.49	225.80	255.62	562.05	982.80	1330.28	1845.69	3263.28	3521.73
4	1015	1106.05	582.46	1.05	4.59	178.87	213.02	659.05	1025.91	1407.61	1847.51	2920.71	4018.96
5	849	1155.30	620.52	1.15	4.80	173.65	256.20	703.53	1068.53	1444.87	1939.10	3284.46	3922.99
6	219	1372.71	736.53	0.78	3.14	184.76	197.36	843.12	1184.31	1838.70	2457.88	3377.84	3521.73
7	1399	1372.47	667.78	0.71	3.40	171.33	260.21	884.84	1288.12	1760.87	2314.62	3284.64	3937.52
8	138	1477.88	719.07	0.24	2.51	182.36	213.72	961.53	1506.44	1965.08	2386.78	3115.50	3446.88
9	503	1493.39	737.09	0.66	3.18	169.40	234.27	972.79	1389.71	1924.22	2518.73	3596.32	3920.71
10	120	1325.37	698.42	1.16	4.80	202.75	232.49	865.57	1249.11	1601.31	2336.50	3334.84	4087.85
11	142	1434.94	753.22	1.06	3.99	235.68	312.28	945.03	1290.47	1778.06	2545.83	3577.44	3939.62
12	210	1502.60	820.46	0.98	3.64	214.54	303.00	913.07	1307.69	1966.88	2778.93	3723.30	4553.01
13	854	1456.40	652.30	0.89	4.24	168.30	275.81	1032.14	1338.06	1807.11	2364.79	3474.98	4193.95
14	658	1555.28	701.36	0.67	3.56	178.06	267.25	1085.96	1493.35	1934.30	2504.76	3537.81	4049.72
15	1111	1621.95	712.41	0.68	3.55	163.88	280.16	1153.21	1504.59	2019.98	2609.54	3634.63	4203.73
16	114	1855.61	949.38	0.35	2.14	308.26	400.73	1034.06	1731.10	2554.61	3211.10	3758.60	4296.30
17	463	1807.33	788.71	0.43	3.03	170.43	248.90	1246.14	1763.87	2249.76	2918.59	3961.48	4129.23
Total	8197	1407.38	714.80	0.82	3.65	163.88	245.20	899.15	1301.05	1802.53	2373.32	3502.94	4553.01

Table 3.7: *Summary statistics of labor income by types, partitioned through Machine Learning Technique. Labor income is adjusted for the age of the individuals. Source: Our elaboration from UK Understanding Society (2009–2011).*

Once this alternative type partition is defined, we proceed to the estimation of elasticity, obtaining results that are slightly different but broadly consistent with the baseline. These are reported in Table 3.8 and illustrated in Figure 3.12.

Looking at both the table and Figure 3.12a, we again observe that median elasticity values tend to decrease as parental occupation increases. At the same time, the boxplots suggest some differences in dispersion: whiskers tend to be shorter for individuals with high parental occupation, indicating more stability in the steepness of the inverse CDFs. Moreover, within these groups, whiskers appear shorter for males than for females (apart from type 10), pointing to a lower variability in male distributions. Overall, the general pattern remains broadly consistent with what was observed in the baseline analysis.

As in Figure 3.3a, the slope boxplots again appear to show higher values toward the right, with greater opportunity sets associated with slightly higher central tendencies. This repeated pattern reinforces the earlier evidence, as the variability observed among types with higher parental occupation once more seems broadly consistent with the behavior of elasticity, both in this robustness check and in the baseline analysis.

To conclude, Figure 3.12b once more shows the boxplots of slope and elasticity across percentiles of the aggregate effort distribution. Similar to the analysis based on manual types (Figure 3.3b), the two measures exhibit closely aligned patterns, both generally increasing with effort. Elasticity tends to grow and display higher variability at upper levels of effort, while the slope follows a broadly comparable trajectory, with some divergences in the lower percentiles.

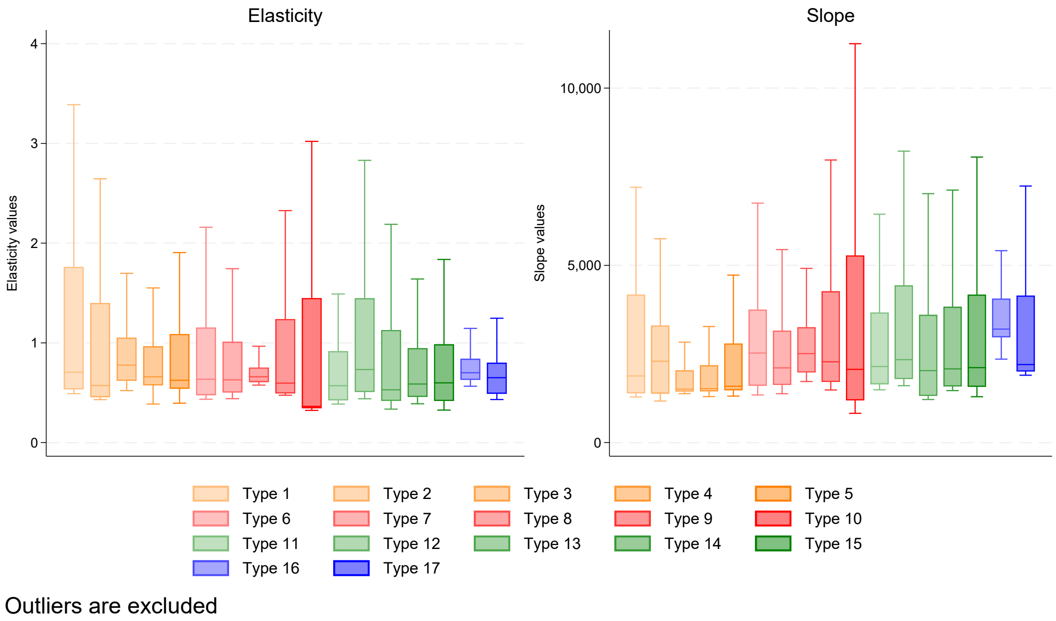
According to these findings, we can argue that, for our sample, the results are not primarily driven by the choice of type partitioning. However, the situation might change when considering a different set of circumstances or a different threshold for the minimum number of observations per type, as this represents a common issue in the equality of opportunity literature.

Table 3.8: *Summary statistics of elasticity by ML types*

ML Type	N	Mean	SD	Skewness	Kurtosis	Min	p1	p25	p50	p75	p90	p99	Max
1	133	1.2754	1.5461	4.6866	29.5357	0.4908	0.4910	0.5337	0.7051	1.7619	2.2455	10.7023	11.9502
2	139	1.1113	1.4054	4.9394	32.2658	0.4309	0.4309	0.4564	0.5722	1.4004	1.9317	8.7496	11.6293
3	130	1.6986	2.7017	3.5778	16.8682	0.5220	0.5225	0.6200	0.7766	1.0529	4.3895	13.9068	17.5000
4	1015	1.5924	4.5559	12.9076	229.9138	0.3864	0.3866	0.5735	0.6592	0.9654	2.8026	16.9131	98.4415
5	849	1.3985	2.5206	6.2793	62.9829	0.3947	0.3950	0.5402	0.6248	1.0889	2.4366	13.1524	37.4629
6	219	1.1559	1.3780	3.7063	18.9490	0.4346	0.4346	0.4758	0.6352	1.1544	2.4512	7.4703	9.6780
7	1399	1.2952	2.6621	10.3219	154.8038	0.4405	0.4408	0.5014	0.6291	1.0112	2.2539	11.6383	51.8670
8	138	1.0340	1.4671	5.7153	40.0491	0.5762	0.5762	0.6070	0.6600	0.7528	1.2826	7.0463	13.1108
9	503	1.2320	1.9654	6.4305	53.5279	0.4749	0.4753	0.4923	0.5963	1.2385	2.1575	12.1885	21.6152
10	120	1.1588	1.7838	4.7506	33.9191	0.3228	0.3230	0.3451	0.3632	1.4490	2.7443	7.5879	15.1251
11	142	1.1185	1.5621	3.5726	17.2002	0.3865	0.3872	0.4233	0.5704	0.9167	2.8726	7.4307	10.7961
12	210	1.4229	3.4662	9.8452	109.5734	0.4396	0.4396	0.5067	0.7327	1.4473	2.4159	9.2986	42.9141
13	854	1.3342	3.3820	8.1555	80.7691	0.3353	0.3354	0.4179	0.5288	1.1291	2.0532	18.3389	44.1852
14	658	1.2165	2.1197	6.6977	63.8644	0.3893	0.3895	0.4575	0.5872	0.9470	2.6514	10.0808	28.2899
15	1111	1.1963	2.1972	7.6553	86.2253	0.3258	0.3259	0.4174	0.5988	0.9853	2.4256	10.1782	33.9308
16	114	0.9973	1.0288	6.1012	49.5667	0.5650	0.5651	0.6287	0.7005	0.8404	1.7081	3.6346	9.8292
17	463	1.1316	1.5753	5.0497	35.1283	0.4320	0.4320	0.4897	0.6509	0.8007	2.6201	10.2581	14.1887
Total	8197	1.3028	2.7785	12.2644	268.1210	0.3228	0.3301	0.4849	0.6296	1.0385	2.3617	11.9502	98.4415

Note: Descriptive statistics for `elasticity` by type, defined through Machine Learning. Source: our elaboration from UK Understanding Society (2009–2011).

(a) ***Panel A: Elasticities and Slopes by ML Types***



(b) ***Panel B: Elasticities and Slopes Distribution (ML)***

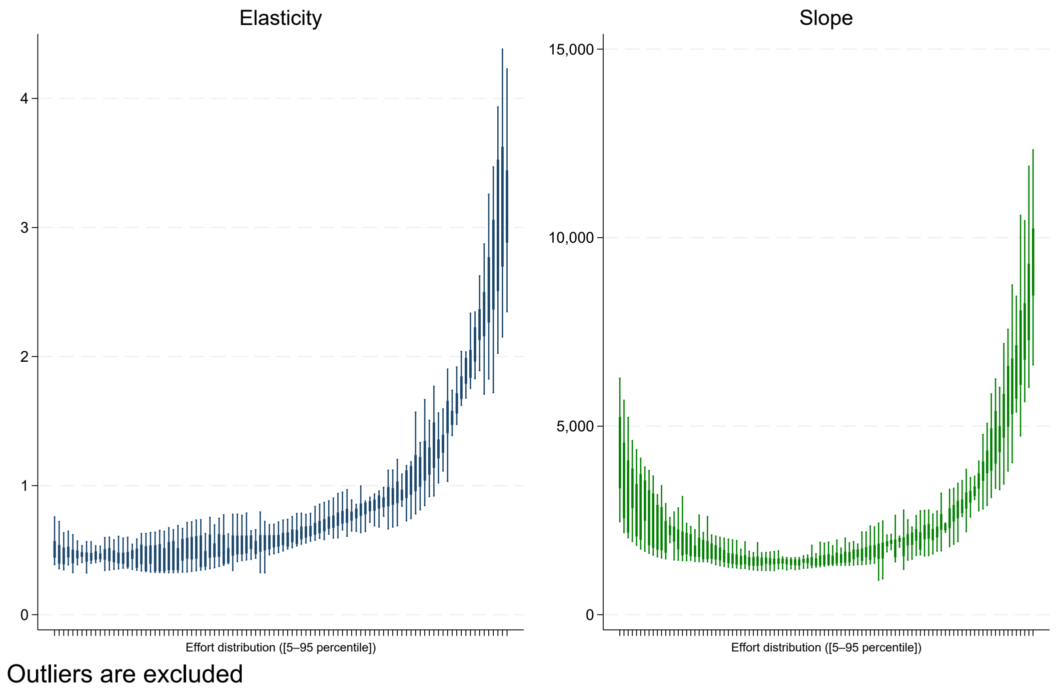


Figure 3.12: *Boxplots of elasticity–slope by ML types (Panel A) and distribution across effort (Panel B). Source: our elaboration from UK Understanding Society (2009–2011).*

3.4 Conclusion

This work was aimed at deriving a positive measure of the extent to which individuals can influence their income by varying their effort and conditional on their background circumstances.

Hence starting from the IOp framework and dividing the population into "types", we began by illustrating how the outcomes variable (labor income) is distributed across the different types by estimating Adaptive Kernel densities and the corresponding inverse CDF of the type-specific income distribution. As done in the literature, this estimation allows us to visualize the type-specific opportunity sets, from which we derived a comparable measure of degree of efforts using the Roemer Identification Assumption. RIA tells us that people at the same percentile of their type's income distribution have exerted the same degree of responsibility. Hence a small movement among percentiles represents a change in degree of effort that individuals exerted and, arguably, the changes in income individuals obtain can then represent the changes in the Sensitivity to effort for each specific type. Using the first wave of UK Understanding Society, we then derived the related measure of slopes and elasticity of outcome variables with respect to a (percentage) change in degree of effort exerted (i.e. a movement across percentiles).

Overall, our analysis shows that sensitivity to effort varies substantially both within types and across the effort distribution. Differences become more evident in the upper part of the distribution, where both elasticity and slope display asymmetric and skewed patterns, with values generally increasing as effort and income rise. The tails of the distribution remain particularly exposed to extreme values, which makes them less stable and more difficult to interpret.

When comparing across types, the general distributional shape is similar, skewed and mainly concentrated between the 25th and 75th percentiles. However, important differences emerge in the levels and dispersion. Types with higher parental occupation levels typically show lower median elasticity and narrower interquartile ranges, suggesting greater stability in their outcome–effort relationship. By contrast, UK females with low parental occupation levels tend to display greater variability and more extreme values, while non-UK males generally exhibit more consistent patterns, particularly in the central percentiles. These findings indicate that both gender and parental occupation matter, shaping not only the average returns to effort but also the stability of these returns across the distribution.

As these patterns suggest that higher rewards to effort do not necessarily correspond to greater sensitivity to effort, we further explore this point through pairwise comparisons. With respect to that, we show how males often display higher average outcomes than females, but without clear differences in responsiveness to effort. Likewise, differences in parental occupation indicate that greater advantages in average income does not always imply higher sensitivity, which may instead be concentrated in specific parts of the effort distribution.

Finally, we compare UK-born individuals with those born abroad among males with high parental occupation. The results suggest that non-UK individuals tend to achieve slightly higher rewards and greater sensitivity to effort, although these patterns are not pronounced.

Taken together, the evidence suggests that sensitivity to effort may capture an additional dimension of inequality of opportunity. This dimension does not always align with the observed reward to effort and may highlight vulnerabilities in specific groups and at particular points of the effort distribution. Importantly, the main results are confirmed when adopting an alternative type partitioning based on machine learning and when using a different outcome variable, namely total net monthly income.

Nevertheless, caution is required in interpreting these findings. Elasticity estimates remain sensitive to extreme values—particularly in the upper tail of the distribution—and depend on methodological choices such as the estimation procedure for the probability density functions (PDFs) and the construction of confidence intervals.

A further limitation of these measures concerns their dependence on the circumstances used to define types, a well-known issue in the equality of opportunity literature. The normative choice of which circumstances to include, as well as the number of observations available within each type, can shape the resulting elasticity measures in different ways. While the latter issue can, at least in part, be addressed through machine learning techniques, further research is needed on how to derive this measure using alternative approaches, exploring heterogeneity across different sets of circumstances and comparing the results obtained.

Finally, in line with Roemer (1998), we suggest that this measure could serve as a useful complement to other individual-level indicators of opportunity deprivation, such as the fairness gap. Taken together, these tools may provide a richer understanding of how inherited circumstances contribute to current economic disparities.

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3.5 Appendix

3.5.1 Preliminary Logarithmic transformation

Income distributions are often skewed and heavy-tailed, which can often distort smoothing estimates of the Cumulative distribution functions. To avoid these problems, we could also apply a preliminary logarithmic transformation of the income variable before applying Kernel Density Estimation, as discussed in Charpentier & Flachaire (2015) and Ahamada & Flachaire (2010), to which we refer for a more comprehensive discussion. This method addresses issues with standard KDE that struggles with multimodal and heavy-tailed distributions, providing a better fit for estimating income density functions. Moreover, Log-transformed distribution leads to smoother boundaries, lower variance, and more stable distribution compared to non-transformed ones, which have a problematic long right tail. Finally, we recall that the log of income has been shown to be a proxy for the utility of income (Easterlin (2005); Layard (2006); Van de Gaer & Ramos (2020) among others).
Therefore, we apply the methodology described in the previous section considering that the Kernel Smoothed CDF computed will be based on logarithmic scale.
More formally:
If effort is defined by the Cumulative Distribution Function (CDF) of income, depending on the type of belonging, and income is preliminarily transformed into its logarithmic form, then the Cumulative Distribution Function obtained through the Kernel Estimation technique will define the opportunity space in the logarithmic domain.

Let us suppose that $\log(y)$ is our relevant variable, where y represents an individual's income.

Then, if effort is defined by the percentile π_t of the income distribution, depending on the type of belonging, and the CDF of our variable is in logarithmic form, effort will be measured as:

$$\pi_t = \tilde{F}_t(\log(y)) \tag{3.7}$$

The function is defined as:

$$\pi_t = \tilde{F}_t(\log(y)) \tag{3.8}$$

where the function $\tilde{F}_t(\cdot)$ represents the Cumulative Distribution Function (CDF) estimated through the Kernel approach.

Recalling that:

$$\log(y) = \tilde{F}^{-1}(\pi_t) \tag{3.9}$$

and differentiating with respect to $\log(y)$, we obtain:

$$1 = \frac{d\tilde{F}_t^{-1}(\pi_t)}{d\pi_t} \cdot \frac{d\tilde{F}_t(\log(y))}{d\log(y)} \tag{3.10}$$

Rearranging the terms:

$$1 = \frac{d\log(y)}{d\pi_t} \cdot \frac{d\tilde{F}_t(\log(y))}{d\log(y)} \tag{3.11}$$

From which we derive the local *Sensitivity to effort* measure as:

$$\frac{d\log(y)}{d\pi_t} = \frac{1}{\frac{d\tilde{F}_t(\log(y))}{d\log(y)}} \quad [c] \tag{3.12}$$

As before, we acknowledge potential measurement issues, and we derive an elasticity measure:

$$\text{elasticity} = \left(\frac{d\log(y)}{d\pi_t}\right) \cdot \frac{\pi_t}{\log(y)} \quad [d] \tag{3.13}$$

If instead of focusing on the log of income we want to go back to the real value of it, we then have to do a further step.

Starting from effort defined as above, we will have:

$$\pi_t = \tilde{F}_t(\log(y)) \tag{3.14}$$

From which we can obtain the log of our outcome (but not the outcome) from its inverse:

$$\log(y) = \tilde{F}_t^{-1}(\pi_t) \tag{3.15}$$

From here, to obtain the value of the slope of the opportunity set, we could either follow the mentioned step above and obtain the measure of the local Sensitivity to effort in utility form (logarithm of income), or we could obtain such value in the real value of income.

To do so, we know from income properties that:

$$\log(a) = b \quad \text{then for natural logarithm we have} \quad a = e^b \tag{3.16}$$

Therefore, for our example:

$$y = \exp\left[\tilde{F}_t^{-1}(\pi_t)\right] = \exp\left(\tilde{F}_t^{-1}\left(\tilde{F}_t(\log(y))\right)\right) \tag{3.17}$$

From which we can obtain, through derivation:

$$1 = \exp\left[\tilde{F}_t^{-1}(\pi_t)\right] \cdot \frac{d\tilde{F}_t^{-1}(\pi_t)}{d\pi_t} \cdot \frac{d\tilde{F}_t(\log(y))}{d\log(y)} \cdot \frac{1}{y} \tag{3.18}$$

Recalling that

$$y = \exp\left[\tilde{F}_t^{-1}(\pi_t)\right], \tag{3.19}$$

we then substitute, eliminate the two y, and obtain:

$$1 = \frac{d\tilde{F}_t^{-1}(\pi_t)}{d\pi_t} \cdot \frac{d\tilde{F}_t(\log(y))}{d\log(y)} \tag{3.20}$$

From which we can derive:

$$\frac{d\log(y)}{d\pi_t} = \frac{d\log(y)}{dy} \cdot \frac{dy}{d\pi_t} = \frac{1}{y} \cdot \frac{dy}{d\pi_t} \tag{3.21}$$

Therefore, the measure of the slope will then be:

$$\text{slope} = \frac{dy}{d\pi_t} = \frac{y}{\frac{d\tilde{F}_t(\log(y))}{d\log(y)}} \tag{3.22}$$

which will give us the measure of how much, given your type, individuals can change their outcome by changing the degree of responsibility characteristics.

As before, to obtain a measure without unit sensitivity, we compute the elasticity of outcome with respect to effort:

$$\text{elasticity} = \frac{dy}{d\pi_t} \cdot \frac{\pi_t}{y} = \frac{\pi_t}{\frac{d\tilde{F}_t(\log(y))}{d\log(y)}} \tag{3.23}$$

3.5.2 Income components and descriptive of incomes

Quoting from the official source explaining our income variable in our dataset, it is constructed as the sum of the six income components described below:

- Labor income: Sum of net pay from usual job, self-employment, and second job.
- Miscellaneous income: Includes various payments like educational grants and it is assumed net of tax.
- Private benefit income: Includes payments like trade union fees and it is assumed net of tax.
- Investment income: Includes pensions, rents, and savings, assumed mostly net of tax.
- Pension income: Includes pensions from previous employers, assumed net of tax.
- Social benefit income: Includes various benefits like state retirement pensions, widow pension, child tax credit, income support, job seeker's allowance and so on. It is assumed as net of tax.

Table 3.9: *Descriptive statistics of income components*

Component	**Share (%)**	**Mean**	**Median**	**Min**	**Max**	**Total N**
Labor income	100.00	1309.52	1200.00	162.50	3794.00	8197
Miscellaneous income	1.62	267.89	216.67	1.67	1300.00	8197
Private benefits	4.07	302.07	216.67	5.42	2360.00	8197
Investment income	27.96	105.41	8.81	0.01	4000.00	8197
Pensions	0.87	561.15	434.00	40.00	3033.34	8197
Social benefits	25.81	431.26	296.67	1.00	2830.00	8197
Total net monthly income	100.00	1453.41	1310.83	169.56	4897.70	8197

Note: The "Share" column indicates the percentage of individuals receiving each income component. All statistics are conditional on the component being strictly positive. Source: our elaboration from UK Understanding Society (2009-2011).

3.5.3 Age adjustment Procedure

For the sake of clarity, we first show, below in this paragraph, the estimates of our age adjustment procedures, showing first the OLS model measured and then the coefficients.

Following the latest work on EoP by Palomino *et al.* (2020); Brunori & Neidhöfer (2021); Brunori *et al.* (2023a), the age adjustment procedure is obtained by regressing the log of our outcome on age and age squared, centered with respect to the median age of the sample, and using the sum of the constant and the residual as the adjusted variable.

We center with respect to the median age of the sample following the literature on intergenerational mobility (Haider & Solon (2006); Almås & Mogstad (2012); Salas-Rojo & Rodríguez (2022) among many others). This literature suggests that centering with respect to the median age of a sample representing a working-age population allows meaningful comparisons among individuals at different stages of their life cycle, using the peak of their predicted income as a reference point. In our sample, the median age is 36, as we can see from the table below.

Percentiles	**Age**	**Summary Stats**	
1%	20	*Obs*	8,197
5%	22	*Sum of wgt.*	8,197
10%	23	*Mean*	36.73734
25%	27	*Std. dev.*	10.83953
50%	**36**	*Variance*	117.4953
75%	46	*Skewness*	0.2786847
90%	52	*Kurtosis*	1.917163
95%	55	*Largest*	59
99%	59		

Table 3.10: *Summary statistics for age on the sample of our analysis. Source: author's elaboration from UK Understanding Society (2009–2011).*

We estimate the age at which our sample reaches, on average, the peak by estimating a simple OLS model as the following:

$$\log Y = \beta_0 + \beta_1 \text{age} + \beta_2 \text{age}^2 + \varepsilon,$$

The results of the regression are as follows.

Variable	**Coefficient**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**
a_age_dv	0.0566858	0.0044678	12.69	0.000	0.0479278 ; 0.0654438
age_squaredlab	-0.0006903	0.0000579	-11.92	0.000	-0.0008038 ; -0.0005768
_cons	5.961445	0.0808531	73.73	0.000	5.802953 ; 6.119938

Table 3.11: *Regression results for `log_lab` on `a_age_dv` and `age_squaredlab`. Number of observations = 8,197.* $R^2 = 0.0224$. *Source: author's elaboration from UK Understanding Society (2009–2011).*

The maximum age is calculated as follows:

$$\text{age\_max} = \frac{-\beta_{\text{a\_age\_dv}}}{2 \cdot \beta_{\text{age\_squaredlab}}}$$

Substituting the estimated coefficients:

$$\text{age\_max} = \frac{-0.0566858}{2 \cdot (-0.0006903)} \approx 41.06$$

Thus, the maximum age is approximately $\boxed{41.06}$.

we see that the age at which maximum **Labor Income** is observed is approximately 40 years, a value close to the median age. Thus we can reasonably center with respect to the median.

At this point, we run the age adjustment procedure by estimating the OLS with centered age as the explanatory variable and taking the sum of the residual and the constant as the income-adjusted variable.

Hence, we run:

$$\log(Y) = \beta_0 + \beta_1\,\text{age}_{\text{centered}} + \beta_2\,\text{age}^2_{\text{centered}} + \varepsilon. \tag{3.24}$$

Our outcome variable will then be:

$$Y_{\text{adjusted}} = \exp\left(\beta_0 + \varepsilon\right). \tag{3.25}$$

Table 3.12: *OLS Regression Results for `log_lab` (Labor Income)*

	(ln)_labor income
age_centered	0.00698***
	(0.000631)
age_centered # age_centered	-0.000690***
	(0.0000579)
Constant	7.107***
	(0.00912)
Observations	8,197

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01 .

3.5.4 Results on total net income : Elasticity and slopes by types

We here replicate the analysis represented in the main text focusing on total net monthly income as our outcome variable. The income variable is obtained by asking individuals to respond in detail to different modules asking the multiple sources of income described above where, to ensure accuracy, respondents are asked to check with financial documents during interviews and interviewers help estimating amounts when necessary and perform checks to validate the consistency of the data reported.

Missing values are then imputed by the institute using, among other techniques, regression analysis, with the usual covariates such as education, age, gender, ethnicity as predictor.

For completeness, we also replicate the same age-adjustment procedure for total net monthly income, in log form. We estimate first the OLS regression of log income on age and age squared:

$$\log Y = \beta_0 + \beta_1 \, \text{age} + \beta_2 \, \text{age}^2 + \varepsilon,$$

with results reported in Table 3.13.

Variable	**Coefficient**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**
a_age_dv	0.0902723	0.0038139	23.67	0.000	0.0827962 ; 0.0977485
age_squared	-0.0010939	0.0000494	-22.12	0.000	-0.0011908 ; -0.0009970
_cons	5.472468	0.0690191	79.29	0.000	5.337173 ; 5.607763

Table 3.13: *Regression results for* `log_income` *on* `a_age_dv` *and* `age_squared`*. Number of observations = 8,197.* $R^2 = 0.0756$*. Source: author's elaboration from UK Understanding Society (2009–2011).*

The estimated peak of income is:

$$\text{age\_max} = \frac{-\beta_{\text{a\_age\_dv}}}{2 \cdot \beta_{\text{age\_squared}}} = \frac{-0.0902723}{2 \cdot (-0.0010939)} \approx 41.26.$$

As with labor income, the turning point is close to the median age of the sample, which justifies centering with respect to the median.

We then re-estimate the model using age centered at the median:

$$\log(Y) = \beta_0 + \beta_1 \, \text{age}_{\text{centered}} + \beta_2 \, \text{age}^2_{\text{centered}} + \varepsilon,$$

with results in Table 3.14.

Variable	log_income
age_centered	0.0115***
	(0.000539)
age_centered # age_centered	-0.00109***
	(0.0000494)
Constant	7.305***
	(0.00779)
Observations	8,197

Table 3.14: *OLS regression results for `log_income` with age centered at the median. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Source: author's elaboration from UK Understanding Society (2009–2011).*

Summary Statistics of total net income by Type

Type	N	Mean	SD	Skew.	Kurt.	Min	p1	p25	p50	p75	p90	p99	Max
1	28	1428.7	666.15	0.55	2.46	353.97	353.97	892.15	1347.77	1809.25	2401.67	2832.33	2832.33
2	105	1476.22	662.66	0.63	3.23	223.39	268.81	1025.36	1337.47	1874.71	2348.67	3303.57	3383.03
3	139	1562.29	642.67	0.53	2.83	252.68	293.27	1087.08	1477.02	1965.52	2447.33	3244.68	3343.50
4	219	1634.02	759.75	0.68	3.08	242.56	365.62	1095.63	1478.33	2141.99	2743.97	3816.19	4128.74
5	138	1734.20	758.90	0.08	2.44	217.72	252.34	1216.99	1782.01	2264.93	2689.62	3429.17	3755.14
6	130	1390.27	693.45	1.04	4.29	331.36	331.36	917.60	1313.41	1671.17	2344.78	3317.30	3886.90
7	1015	1449.40	633.26	0.86	4.18	225.90	355.06	1012.54	1356.02	1804.23	2305.36	3490.45	4231.35
8	849	1486.57	674.56	1.24	5.70	226.19	339.91	1031.92	1365.52	1814.03	2273.99	3757.26	5061.57
9	1399	1676.93	682.33	0.89	4.56	214.67	441.80	1199.27	1592.31	2051.23	2587.18	3767.67	5236.66
10	503	1801.79	726.59	0.62	3.35	254.41	499.67	1295.63	1715.41	2198.74	2822.01	3719.24	4569.30
11	33	1330.97	630.75	0.99	4.72	333.25	333.25	883.08	1304.13	1630.75	1948.84	3355.69	3355.69
12	87	1522.90	752.48	1.20	4.68	230.06	230.06	995.36	1346.58	1877.57	2732.89	4386.45	4386.45
13	142	1569.45	770.88	1.05	4.24	233.93	349.45	1066.78	1456.38	1958.46	2545.83	3728.98	4333.48
14	210	1649.34	867.47	1.09	4.22	296.89	405.07	1034.02	1473.64	2087.09	3078.59	4173.66	5193.24
15	114	2031.47	1042.17	0.48	2.57	313.61	407.70	1182.45	1976.44	2766.43	3374.72	4567.02	4904.58
16	98	1488.12	647.68	0.46	2.60	308.96	308.96	994.07	1331.02	1962.48	2359.95	2981.61	2981.61
17	756	1633.58	715.01	1.14	5.42	180.11	366.22	1164.56	1505.12	1988.68	2539.98	4119.33	5332.52
18	658	1700.82	753.95	0.90	4.52	204.00	308.33	1211.93	1611.61	2075.76	2663.18	4198.51	5150.69
19	1111	1777.17	762.70	0.84	4.06	167.45	363.29	1272.64	1649.40	2185.49	2797.24	4037.55	4846.94
20	463	1990.27	854.08	0.55	3.30	168.45	291.17	1389.23	1938.12	2439.60	3189.29	4454.52	4653.21
Total	8197	1652.89	739.96	0.91	4.28	167.45	342.35	1148.33	1537.01	2054.50	2631.73	3901.87	5332.52

Table 3.15: *Summary statistics of adjusted net income by* `types`*. Source: author's elaboration from UK Understanding Society (2009–2011).*

Summary Statistics of elasticity defined on total net income by Type

Type	N	Mean	SD	Skewness	Kurtosis	Min	p1	p25	p50	p75	p90	p99	Max
1	28	1.1228	0.4949	0.630	2.48	0.561	0.561	0.684	1.089	1.408	1.791	2.218	2.218
2	105	1.1673	1.4758	3.506	16.39	0.308	0.308	0.372	0.633	1.333	1.907	8.243	8.934
3	139	0.8961	1.0162	3.651	18.23	0.305	0.306	0.375	0.649	0.816	1.617	5.985	7.020
4	219	1.0948	2.0369	7.524	69.63	0.358	0.358	0.402	0.671	0.887	2.353	12.301	22.554
5	138	0.9233	1.8066	9.547	102.23	0.501	0.501	0.524	0.568	0.681	1.228	5.961	20.517
6	130	1.3510	2.3616	5.730	46.43	0.418	0.418	0.477	0.522	1.057	3.297	7.019	21.946
7	1015	1.3588	3.6292	9.620	119.85	0.374	0.375	0.410	0.510	1.005	2.505	20.885	57.316
8	849	1.4054	4.4459	14.41	263.51	0.336	0.336	0.374	0.544	0.982	2.330	13.468	93.863
9	1399	1.3646	5.1355	15.08	285.02	0.299	0.299	0.355	0.537	0.853	1.884	18.076	118.343
10	503	1.1095	2.5973	10.78	150.09	0.339	0.339	0.375	0.476	1.020	1.905	9.042	42.805
11	33	1.6213	4.2383	3.863	16.91	0.283	0.283	0.325	0.369	0.647	2.107	21.219	21.219
12	87	1.0516	1.8939	6.605	53.86	0.327	0.327	0.346	0.405	1.264	2.680	16.618	16.618
13	142	1.0683	1.7268	5.398	42.15	0.348	0.348	0.381	0.538	0.766	2.589	5.857	16.041
14	210	1.4243	3.5242	8.996	94.23	0.397	0.397	0.464	0.679	1.263	2.620	14.603	41.873
15	114	1.0894	1.3318	4.276	22.40	0.589	0.589	0.645	0.696	0.778	1.494	7.211	9.501
16	98	1.1271	1.6310	2.939	10.18	0.340	0.340	0.438	0.713	0.822	1.909	7.228	7.228
17	756	1.4347	4.3910	10.23	139.59	0.309	0.309	0.370	0.530	1.025	1.712	22.425	76.069
18	658	1.3507	3.2959	9.939	146.04	0.359	0.359	0.426	0.549	0.975	2.138	16.965	58.353
19	1111	1.2731	3.1345	9.240	109.29	0.297	0.297	0.368	0.579	0.938	2.374	12.980	46.310
20	463	1.1418	1.6894	4.640	28.40	0.375	0.376	0.470	0.580	0.896	2.572	11.198	13.996
Total	8197	1.2941	3.6841	14.29	302.41	0.283	0.299	0.397	0.561	0.963	2.168	14.445	118.343

Table 3.16: *Summary statistics of Elasticities (Net income) by types. Source: author's elaboration from UK Understanding Society (2009–2011).*

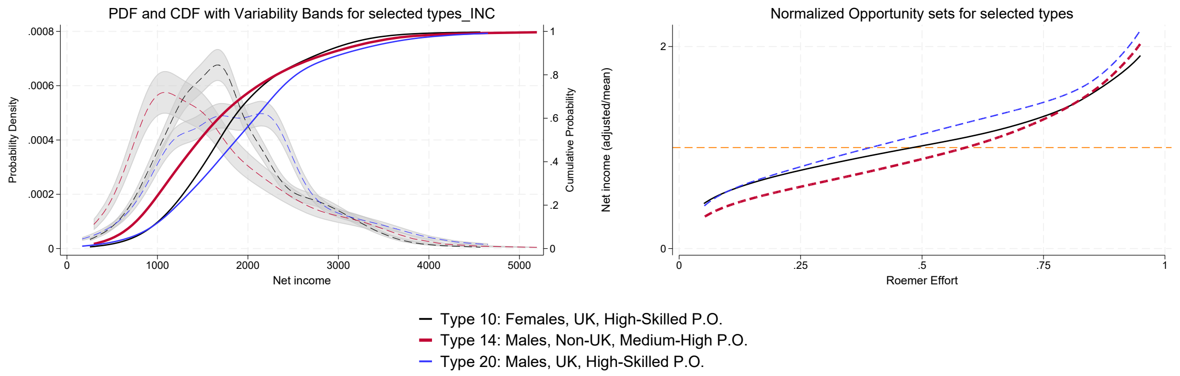
Summary Statistics of slope defined on total net income by Type

Type	N	Mean	SD	Skewness	Kurtosis	Min	p1	p25	p50	p75	p90	p99	Max
1	28	3066.61	1455.43	1.139	3.58	1657.5	1657.5	1794.4	2813.3	3710.4	5060.9	6792.0	6792.0
2	105	4005.49	5077.41	3.332	15.09	983.0	986.9	1242.9	2534.2	3810.7	8616.7	27754.0	30721.2
3	139	3500.11	4410.39	3.813	18.44	1565.2	1565.2	1822.4	1966.9	3208.8	7741.1	24569.7	29453.2
4	219	4358.84	8203.19	7.900	76.35	1543.5	1543.7	1770.9	2407.3	3795.2	8300.5	47492.9	93768.9
5	138	4116.33	6878.22	9.009	94.60	1748.0	1748.1	2021.4	2688.0	3776.8	6759.0	20695.7	77295.5
6	130	4352.65	8516.69	7.133	65.48	1167.4	1167.6	1313.6	1998.3	4115.0	8519.0	23726.0	85599.4
7	1015	4594.01	14012.0	11.35	162.0	1262.1	1262.3	1409.1	1895.7	3163.5	7116.1	73509.9	243166.1
8	849	5153.99	20973.9	16.94	342.3	1218.9	1219.4	1447.0	1868.3	3139.1	8848.9	51201.7	475964.8
9	1399	5474.24	24803.7	17.59	371.3	1356.6	1357.1	1619.7	2078.8	3553.0	7297.0	68758.9	620555.8
10	503	4635.06	11283.4	11.88	180.0	1478.6	1478.9	1651.8	2273.4	4452.9	7540.2	34106.7	196206.0
11	33	6187.80	12430.1	3.313	12.99	765.9	765.9	1080.0	1828.8	4521.7	13007.3	57361.2	57361.2
12	87	4512.80	8443.90	6.695	53.69	1149.8	1149.8	1367.3	2422.4	4233.8	8655.4	73679.0	73679.0
13	142	4558.27	7137.76	6.001	51.64	1547.7	1548.3	1683.7	2017.5	4172.5	11355.1	22387.0	70025.7
14	210	5630.37	17487.4	10.01	113.4	1737.8	1738.1	1889.4	2417.0	4413.2	8806.7	61730.3	218335.6
15	114	5195.17	6168.35	4.657	26.79	2624.8	2624.8	3040.1	3470.8	4417.1	6149.7	33657.9	47212.1
16	98	3855.66	4906.56	2.625	8.801	1420.5	1420.5	1641.7	1963.9	2499.4	11105.8	22016.1	22016.1
17	756	5810.72	20959.0	12.53	203.9	1382.0	1382.0	1459.8	2012.7	3840.1	8159.1	93191.2	406490.6
18	658	5478.26	15275.3	12.59	220.9	1566.3	1566.5	1630.6	2090.8	4266.6	8312.3	71895.2	301115.3
19	1111	5415.86	14314.6	10.25	131.8	1314.2	1314.5	1628.9	2155.4	4187.0	9565.5	52973.8	225107.0
20	463	5189.57	7719.07	4.652	28.73	2011.4	2011.7	2072.8	2333.8	4684.9	11271.6	50503.3	65705.9
Total	8197	5114.55	16980.4	17.80	450.9	765.9	1219.4	1617.0	2104.7	3773.9	8236.6	56653.7	620555.8

Table 3.17: *Summary statistics of Slopes (Net income) by types. Source: author's elaboration from UK Understanding Society (2009–2011).*

Graphical results

(a) *Opportunity sets and CDF/PDF for selected types*



(b) *Elasticities and slopes of Net income vs effort*

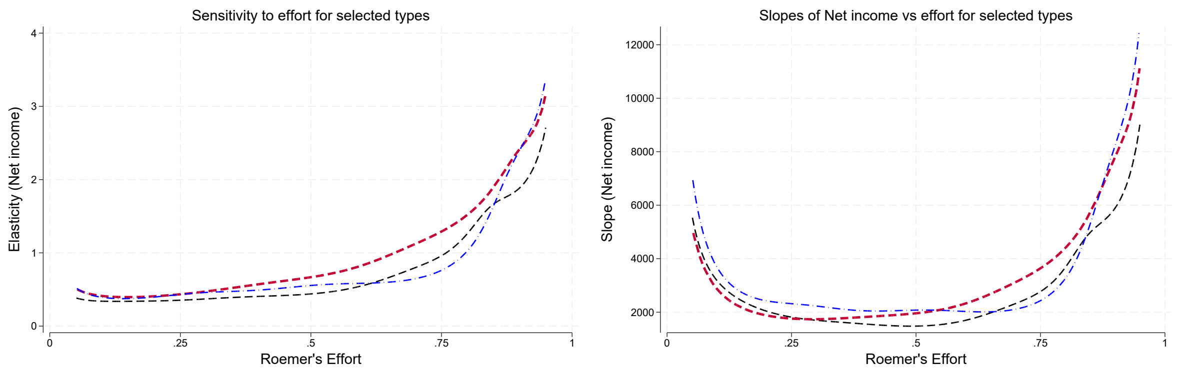


Figure 3.13: *Graphs of Net income by types: (a) opportunity sets with distribution functions, (b) elasticities and slopes with respect to effort.*

3.5.5 Results: Slopes

Table 3.18: *Summary statistics of **slopes** by types*

Type	N	Mean	SD	Skewness	Kurtosis	Min	p01	p25	p50	p75	p90	p99	Max
1	28	3021.08	1419.17	0.88	2.77	1575.52	1575.52	1649.21	2659.70	3743.30	5516.99	6197.83	6197.83
2	105	3677.13	6307.16	5.16	30.32	1106.30	1106.62	1387.41	1805.58	4372.85	5519.15	40907.46	43280.90
3	139	3220.40	4374.50	5.74	40.77	1171.90	1172.38	1382.41	2295.59	3303.93	5119.95	27473.08	38566.52
4	219	3912.73	4689.69	3.94	21.66	1343.02	1343.84	1603.54	2525.21	3753.55	8319.16	25693.32	34536.93
5	138	3757.12	4918.28	5.76	42.89	1722.96	1726.39	1976.94	2510.00	3254.41	6031.50	22371.98	45582.11
6	130	4162.22	8529.57	4.56	25.90	1380.87	1380.88	1436.78	1509.38	2038.18	8875.26	46015.63	62185.87
7	1015	4277.42	16428.95	16.28	344.16	1297.72	1298.48	1444.81	1522.78	2179.40	6382.01	49908.07	396321.09
8	849	3832.02	8469.25	8.51	111.84	1310.19	1310.44	1476.75	1589.02	2796.73	5818.89	43693.39	147327.58
9	1399	4070.85	9629.72	12.48	212.21	1379.21	1379.76	1625.96	2106.76	3157.85	6321.57	38651.18	204651.64
10	503	4269.46	7286.54	7.16	64.28	1484.42	1484.66	1709.47	2279.94	4267.58	7283.26	44335.65	85240.38
11	33	5852.10	10716.63	3.15	12.71	621.67	621.67	1176.25	2610.53	4043.72	16775.07	51924.21	51924.21
12	87	4673.63	7055.55	4.70	31.56	953.34	953.34	1167.73	2093.30	5170.51	9909.60	55006.17	55006.17
13	142	4220.07	5710.21	3.90	21.24	1488.89	1488.98	1643.02	2146.57	3671.91	9501.42	27213.59	43053.46
14	210	5052.07	15395.37	10.56	123.19	1605.66	1605.77	1791.78	2339.71	4433.51	7552.07	35123.93	196238.52
15	114	4311.79	4220.73	6.93	60.87	2353.48	2361.34	2970.58	3201.22	4063.76	6522.99	14113.48	42563.17
16	98	3619.74	5125.59	3.41	13.69	1391.21	1391.21	1533.89	1967.78	2986.81	4974.19	28370.62	28370.62
17	756	4662.81	12539.98	8.50	87.98	1209.19	1209.22	1296.48	2003.11	3704.97	6822.05	61470.42	168286.03
18	658	4366.29	7942.95	7.68	82.41	1467.43	1467.69	1582.38	2079.09	3832.18	8738.08	36111.93	114999.29
19	1111	4498.35	8592.66	8.74	110.46	1294.60	1294.82	1573.59	2114.90	4174.03	8138.52	37436.16	143045.88
20	463	4539.92	6351.37	5.27	38.29	1899.88	1900.36	2003.80	2202.20	4148.11	9129.55	41088.45	59054.98
Total	8197	4254.77	10145.05	14.72	375.63	621.67	1209.25	1527.66	2040.51	3445.71	7283.26	40907.46	396321.09

Note: Descriptive statistics for the variable `slopeLAB_adj`, by type. Reported statistics include the number of observations (N), mean, standard deviation (SD), skewness, kurtosis, minimum, and selected percentiles (p01, p25, p50, p75, p90, p99, and maximum). The last row provides summary statistics over the full distribution. Source: author's elaboration from UK Understanding Society (2009–2011).

Slopes of labor income with respect to effort across selected types

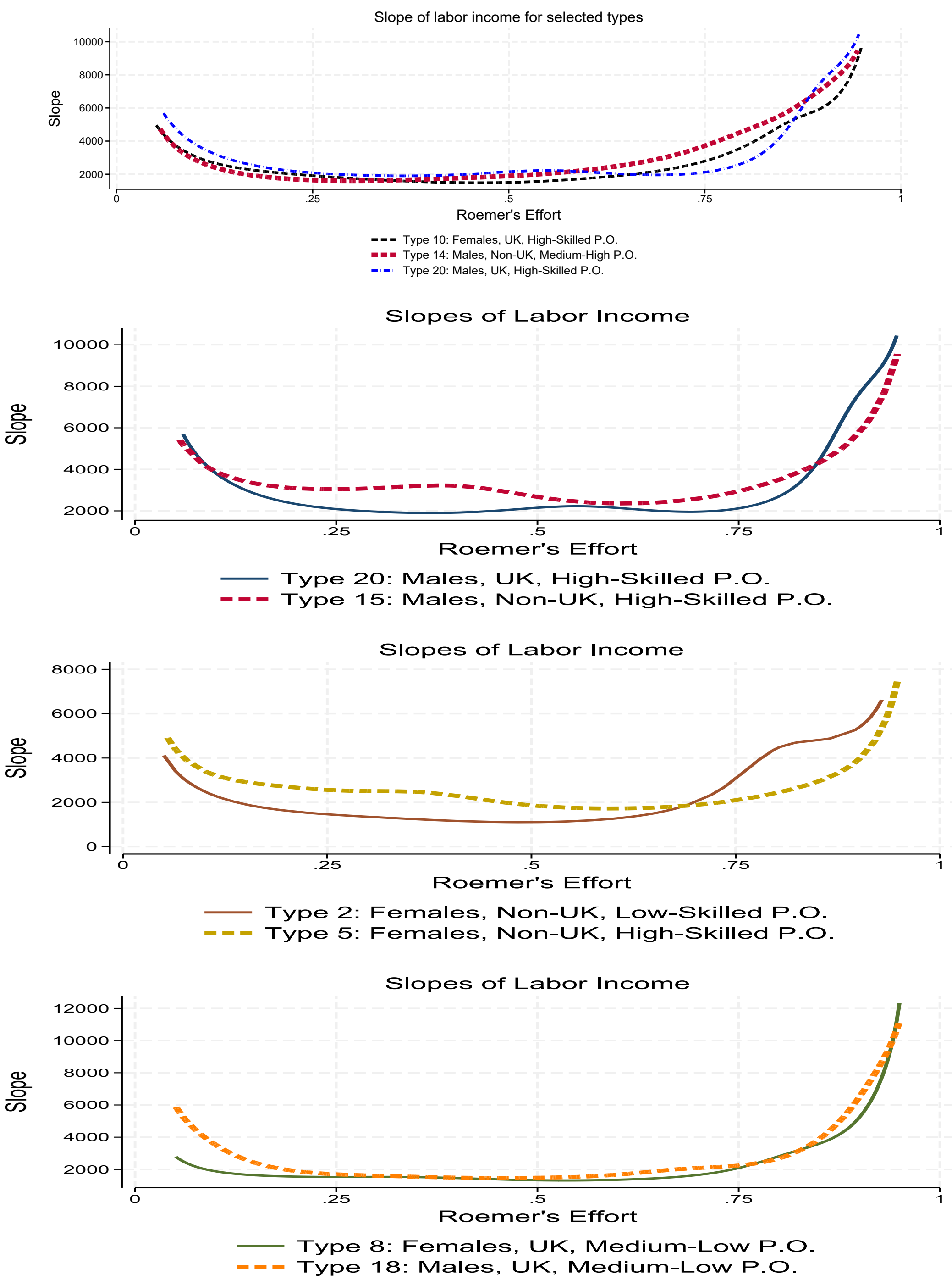
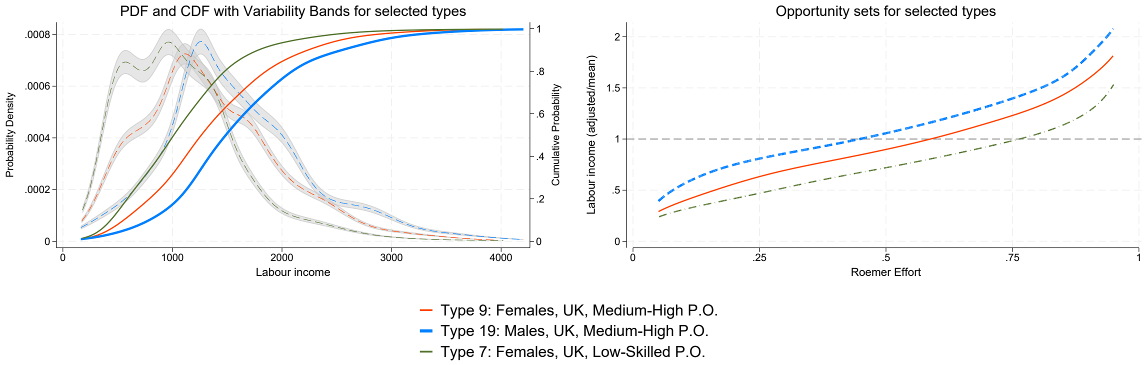
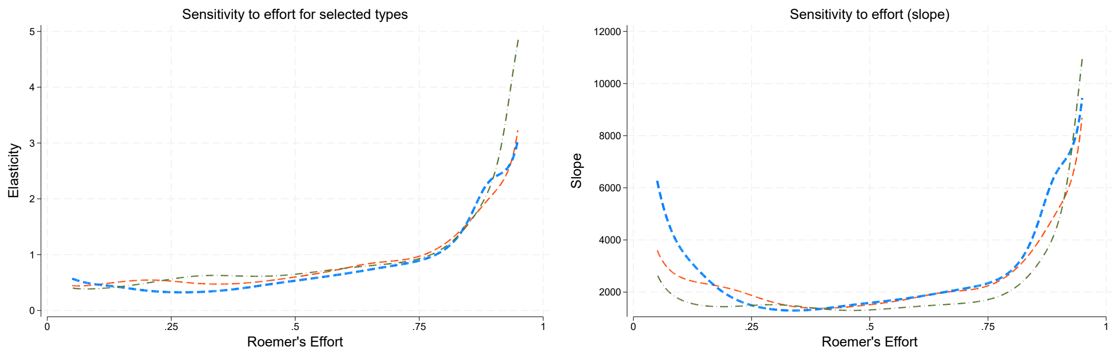


Figure 3.14: *Detailed slope estimates for effort–income relationships by type.*

Results: 3 most numerous types



(a) *PDF and CDF with variability bands (left) and normalized opportunity sets (right) for types 7, 9, and 19.*



(b) *Elasticity (left) and slopes (right) with respect to effort for types 7, 9, and 19.*

Figure 3.15: *Opportunity sets (top) and sensitivity measures (bottom: elasticity and slopes) with respect to effort for the three most numerous types of our sample (7, 9, and 19). Source: our elaboration from UK Understanding Society (2009-2011).*

3.5.6 Robustness: Slope Confidence intervals

Slope Estimates with 90% Confidence Intervals by Type

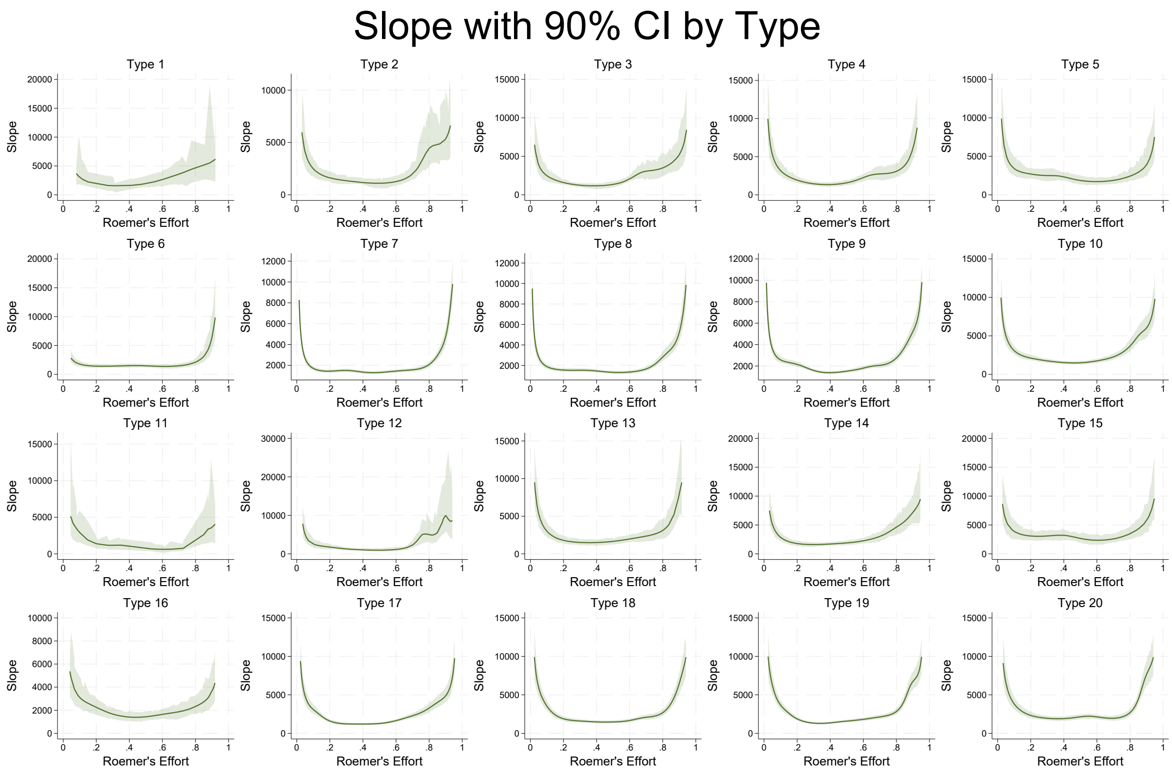


Figure 3.16: *Slope estimates and 90% confidence intervals across the 20 types, based on Roemer's effort distribution. The shaded areas denote 90% confidence intervals. Source: authors' elaboration from UK Understanding Society (2009–2011).*

Panel B1: Slope (Types 10, 14, 20) ***Panel B2: Slope (Types 7, 9, 19)***

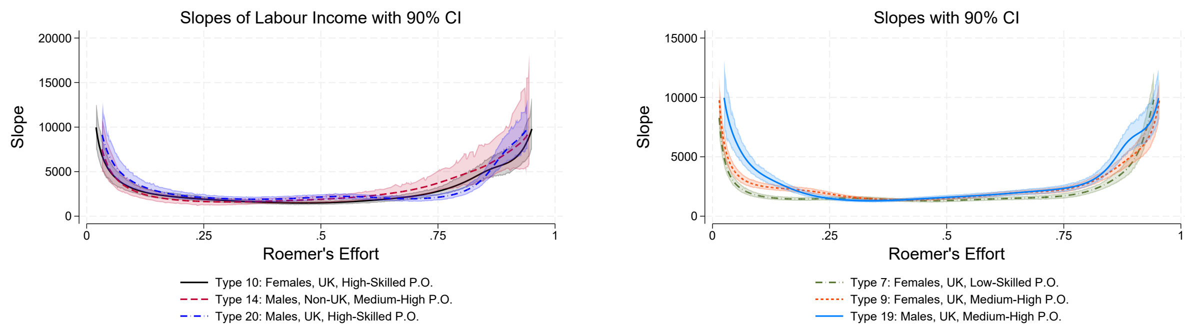
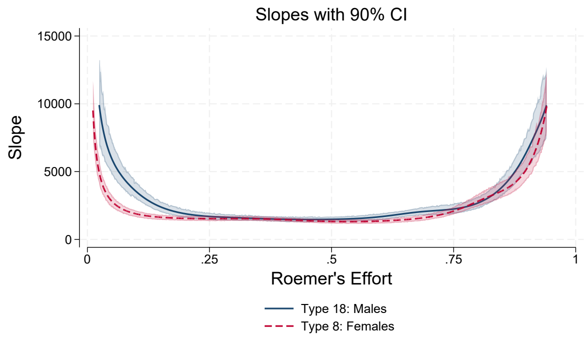


Figure 3.17: *Slope (Panels B1 and B2) with 90% confidence intervals for different type groups. Source: Author's elaboration from UK Understanding Society (2009–2011).*

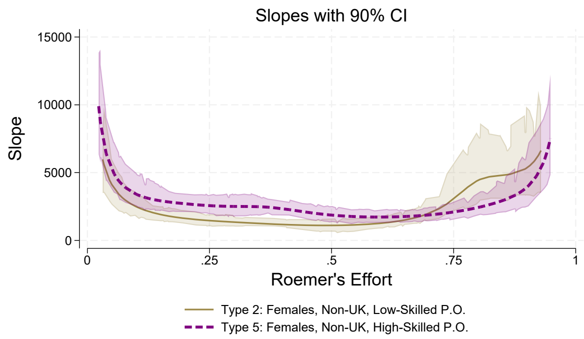
Pairwise Comparisons of Slope with 90% CI

(a) Gender comparison



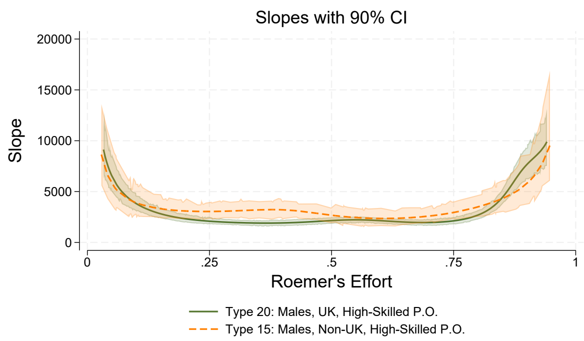
(a) *Males (Type 18) vs Females (Type 8), both UK, Medium-Low P.O.*

(b) Parental occupation



(b) *Females, Non-UK: Low-Skilled P.O. (Type 2) vs High-Skilled P.O. (Type 5).*

(c) UK vs Non-UK



(c) *Males, High-Skilled P.O.: UK (Type 20) vs Non-UK (Type 15).*

Figure 3.18: *Slopes with 90% confidence intervals for three pairwise comparisons: (a) Gender, (b) Parental Occupation, and (c) UK vs Non-UK. Source: Author's elaboration from UK Understanding Society (2009–2011).*

3.5.7 Robustness: Slope with ML types

Table 3.19: *Summary statistics of slopeML by ML types*

ML Type	N	Mean	SD	Skewness	Kurtosis	Min	p1	p25	p50	p75	p90	p99	Max
1	133	3426.51	4770.17	5.52	37.51	1287.84	1290.38	1391.65	1880.15	4175.28	5526.17	34118.15	38736.02
2	139	3220.40	4374.50	5.74	40.77	1171.90	1172.38	1382.41	2295.59	3303.93	5119.95	27473.08	38566.52
3	130	4162.22	8529.57	4.56	25.90	1380.87	1380.88	1436.78	1509.38	2038.18	8875.26	46015.63	62185.87
4	1015	4277.42	16428.95	16.28	344.16	1297.72	1298.48	1444.81	1522.78	2179.40	6382.01	49908.07	396321.10
5	849	3832.02	8469.25	8.51	111.84	1310.19	1310.44	1476.75	1589.02	2796.73	5818.89	43693.39	147327.60
6	219	3912.73	4689.69	3.94	21.66	1343.02	1343.84	1603.54	2525.21	3753.55	8319.16	25693.32	34536.93
7	1399	4070.85	9629.72	12.48	212.21	1379.21	1379.76	1625.96	2106.76	3157.85	6321.56	38651.18	204651.60
8	138	3757.12	4918.28	5.76	42.89	1722.96	1726.39	1976.95	2510.00	3254.41	6031.50	22371.98	45582.11
9	503	4269.46	7286.54	7.16	64.28	1484.42	1484.66	1709.47	2279.94	4267.58	7283.26	44335.65	85240.38
10	120	4814.83	7278.86	4.76	34.56	825.24	826.22	1191.64	2064.84	5281.04	11878.45	25871.54	62339.31
11	142	4220.07	5710.21	3.90	21.24	1488.89	1488.98	1643.02	2146.57	3671.91	9501.42	27213.59	43053.46
12	210	5052.07	15395.37	10.56	123.19	1605.66	1605.77	1791.78	2339.72	4433.51	7552.07	35123.93	196238.50
13	854	4646.28	13078.75	9.12	100.34	1214.50	1214.53	1317.28	2030.71	3603.21	6576.30	64352.18	185847.50
14	658	4366.29	7942.95	7.68	82.41	1467.43	1467.69	1582.38	2079.09	3832.18	8738.08	36111.93	114999.30
15	1111	4498.35	8592.66	8.74	110.46	1294.60	1294.82	1573.59	2114.90	4174.03	8138.52	37436.16	143045.90
16	114	4311.79	4220.73	6.93	60.87	2353.48	2361.34	2970.58	3201.22	4063.76	6522.99	14113.48	42563.17
17	463	4539.92	6351.37	5.27	38.29	1899.88	1900.36	2003.80	2202.20	4148.11	9129.55	41088.45	59054.98
Total	8197	4261.02	10274.79	14.68	366.43	825.24	1215.15	1527.44	2040.35	3446.20	7291.54	40868.79	396321.10

Note: Descriptive statistics for `slopeML` by type, defined through Machine Learning. Source: our elaboration from UK Understanding Society (2009–2011).

General Conclusions

As Europe emerges from the Covid-19 crisis, new geopolitical tensions cast uncertainty over its future, making political trust, social cohesion, and equal opportunities crucial pillars of democratic stability. However, the picture that emerges for government institutions is clear: over the past two decades, citizens' confidence in public bodies has declined significantly.

This dissertation examined some of the main determinants of this trend, focusing on the various socioeconomic shocks that occurred and the ongoing digital transformation. It analysed these dynamics by exploring the interaction between information, inequality, and opportunity as key factors influencing trust in national and supranational institutions, and by proposing new methodological tools to investigate both their individual and societal determinants.

Each chapter approached this general question from a different, yet complementary, perspective, focusing first on the role of the digital platforms and then shifting to the role of socioeconomic inequality.

The first chapter examined how various ways of accessing political information through online platforms—such as social networks and digital newspapers—affect individuals' trust in national political institutions. Using cross-sectional data from a sample of the Italian population over the period 2014–2022, it first compared the association between political trust and the use of the Internet as a source of information, distinguishing between online and offline users. Then, going into further detail, it explored the dual role of social networks and online newspapers on the web.

The OLS regression results show a strong and consistent negative association between the use of the Internet to access political information and individuals' confidence in political institutions. However, this overall relationship hides some countervailing effects that remain even after controlling for endogeneity. Specifically, while reading political news through online newspapers seems to contribute positively to political trust, the use of social networks often exerts the opposite influence, eroding confidence and reinforcing distrust toward political institutions.

Arguably, the structure of newspapers provides a framework in which journalistic standards and professional accountability act as filters against the most harmful distortions of information. Although this does not eliminate bias or partisanship, it tends to promote fact-checking and a clearer distinction between opinion and reporting, as editors face the reputational cost of losing readers when publishing false or misleading news.

By contrast, social networks amplify echo chambers and misinformation. New forms of interaction differ from traditional media, as individuals are both consumers and producers of information within a system characterized by low entry barriers and user profiling. Their algorithms privilege viral and emotional content over accuracy, creating fragmented spaces that reinforce existing biases. Ultimately, these dynamics amplify misinformation and polarization, potentially undermining trust in national political institutions and revealing the Internet's dual nature as both a democratic resource and a potential threat to institutional trust.

For this reason, we argue that further research should be aimed at assessing the role of internet not only as a broad instrument but also in its different usage, especially in the lights of the new social networks emerging.

The second chapter investigated the role of inequality as a determinant of trust in supranational political institutions, offering both a distributive and a welfare perspective and highlighting how inequality shaped citizens' confidence in supranational bodies, particularly the European Parliament, after the recent economic shocks.

To capture these dynamics, the analysis proposed a non-parametric tool, the Trust Dynamics Curve (TDC), designed to consistently measure variations in political trust across socioeconomic groups while addressing some of the methodological limitations of studies based on categorical indicators. Building on this, it further introduced a normative framework to assess the welfare implications of changes in trust, based on the idea that improvements among the most disadvantaged socioeconomic groups are socially preferable, since trust represents an essential component of both individual and collective well-being.

Using data from the European Social Survey, the empirical illustration adopted one of the first distributional perspectives on political trust from a pan-European standpoint. The results show that recent crises—particularly the sovereign debt crisis and the COVID-19 pandemic—may have caused a lasting decline in trust, with middle-income groups and individuals with low parental education being the most affected. Additional analyses on generalized trust and subjective well-being confirm these patterns, pointing to a close connection between trust, inequality, and welfare.

To assess welfare changes, the proposed framework required an ordering of socioeconomic groups. To this end, the chapter compared two alternative forms of partitioning: one based on pure income inequality and the other on inequality of opportunity. As the results seem to differ across these two dimensions, revealing a potential welfare deterioration following the 2010 sovereign debt crisis, factors such as income or socioeconomic conditions beyond individuals' control could play an important role in shaping perceptions toward political institutions.

As the results in Chapter 2 left open the debate, as expected, on the differences between income and opportunity inequality and how these seemed to shape political trust in distinct ways, Chapter 3 shifted the focus to the effect of individual socioeconomic status. Arguably, as a determinant of their political belief, individuals may care not only about their current socioeconomic position but also about their ability to improve it, an idea that is also consistent with the literature on subjective well-being and social capital.

To capture this idea, Chapter 3 proposed a measure of individual sensitivity to effort, aimed at measuring the extent to which people can influence their outcomes given their socioeconomic background. Building on the equality of opportunity literature and Roemer's Identification Assumption, the analysis used adaptive kernel densities to estimate type-specific income distributions and their inverse cumulative distribution functions (CDFs). The slope of the inverse CDF represented the local sensitivity to effort, indicating how much income changes in response to small variations in effort within each type.

Applying this method to the UK Understanding Society data, the results show that sensitivity to effort varies substantially across and within types, being generally higher at the extremes of the effort distribution. Moreover, it provides some insight into the role of parental background, as this appears to be the circumstance showing the highest stability across the sensitivity-to-effort measure. Moreover, comparing different types with one another, these findings reveal that higher rewards to effort do not necessarily correspond to greater sensitivity, potentially highlighting an additional dimension of inequality of opportunity.

As the literature on equality of opportunity is developing individual indicators, and further research is needed to incorporate the role of circumstances into the social capital equation, such measure could be further refined and applied to explore the determinants of political trust and other individual perceptions in future studies.

Taken together, these findings offer new insights into how the information environment and socioeconomic structures interact to shape citizens' attitudes toward governance and institutional legitimacy.

Nevertheless, all three works leave space for future research to be conducted in the near future. Specifically, as Chapter 1 shows the risks associated with the use of the Internet and social networks to obtain information, we cannot claim causality, as is typical of these studies, hence calling for greater robustness in the methodology used and potential extensions. Ideally, a causal framework should allocate information tools randomly across a population, so as to build a credible counterfactual able to detect the average treatment effect of those consuming information on social networks. Alternatively, a more robust econometric study could be based on a panel dataset, thereby controlling for endogeneity problems at the individual level.

In the absence of both potential strategies, Chapter 1 relied on a cross-sectional dataset from ISTAT, attempting to partially correct for endogeneity using Lewbel's method. In the future, since this method cannot control for reverse causality and may not be the best choice when controls are endogenous, the plan is to strengthen robustness, possibly by exploiting other econometric methods such as propensity score matching or instrumental variable that could be suitable for the current dataset.

Simultaneously, the new insights into the dynamics of trust provided by Chapter 2 through the development of the Trust Dynamics Curve (TDC) reveal interesting patterns in both institutional and social trust. However, its results should be interpreted with caution, as confidence intervals are not provided. Moreover, while the TDC can be a useful graphical tool to describe the evolution of indicators before and after a shock, future work should extend the TDC framework to capture the intertemporal dynamics of trust in multiperiod settings, potentially relying on the literature on poverty indexes to further refine the measure and its normative rationale. In addition, a deeper exploration of type partitioning—based not only on arbitrary choices but also on statistical relevance with respect to socioeconomic outcomes—could provide greater statistical robustness to the definition of types, yielding further valuable insights.

This limitation aligns with the robustness of Chapter 3, where the techniques implemented to partition types using Machine Learning methods can certainly support further analyses in both chapters. Specifically, regarding the proposed measure of individual sensitivity to effort, the heterogeneity in the results may depend on both the circumstances under analysis and the outcome selected. With respect to the first aspect, the Transformation Trees could be implemented with a wider interaction of different circumstances while still ensuring a robust number of observations within each type. The second aspect, instead, could raise further questions about the role of welfare in reshaping opportunity sets.

Specifically, while social benefits and taxation can help reduce income inequality and narrow the distance between opportunity sets, little is known about how they may actually change their local shape, which is something that the slope and elasticity proposed in this work could help clarify in the future, especially in light of the potential relationship between this measure of sensitivity to effort and confidence in institutions.

To conclude, the main findings of this analysis invites several considerations: fostering and preserving trust is crucial for the proper functioning of democracy, and its restoration should be pursued through both short- and long-term strategies.

In the short term, policy interventions require stronger regulation of online platforms, particularly during times of crisis. Governments and supranational institutions should enhance transparency, support fact-checking, strengthen digital literacy, and address the socioeconomic roots of disaffection. Only through such coordinated actions can digital innovation become a source of democratic resilience rather than institutional fragility.

At the same time, as highlighted by OECD. (2022), long-term strategies to rebuild institutional trust should address socioeconomic disparities, since inequality is a key factor in fostering resilience against disinformation and sustaining democratic governance.

With respect to this, considering the role that parental background seems to play—both as a determinant of trust and as a crucial factor influencing how much individuals can improve their socioeconomic status through effort—public investment in education appears to be a crucial step to restore trust and level the playing field. As the new generations approach the 2030s, with the challenge of population ageing, environmental issues, and growing psychological concerns, this once again emerges as a key ingredient for a more prosperous and cohesive future.