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Bridging Social Divides: Understanding the Impact of Economic and Social Inequality on Employment in Italy

by

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Abstract This study examines how individual background factors in Italy influence employment quality, focusing on different labour market outcomes, namely income, employment duration, contract type, and part-time work using data from the Survey on Household Income and Wealth (SHIW). Results show that parental education and household wealth impact labour income, with wealth effects diminishing at higher income levels and education more influential in middle to upper percentiles. Gender interacts with socioeconomic background, with women earning less, holding part-time and fixed-term contracts, and facing more job instability. Similar patterns are observed for other vulnerable groups, namely young people, individuals in the South, and unskilled workers. These findings contribute to our understanding of employment quality in Italy and the role of individual background characteristics in shaping labour market outcomes.

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1

Introduction

In a worldwide famous country for its rich cultural heritage and diverse landscape, Italy also struggles with structural economic inequalities that shape the life conditions of its citizens and residents. This thesis goes deep into the intricate relationship between individuals' socioeconomic background and employment quality in Italy. By deploying historical panel data from the Survey on Household Income and Wealth (SHIW) over twenty years of observations, I explore how background factors, like parental education and household wealth class, influence individuals' employment stability. The analysis of the Italian labour market shows interesting patterns: both wealth and parental education play pivotal roles, but their impact varies across the income distribution. While wealth appears to lose its relevance at higher labour income levels, parental education grows in significance in the middle to upper percentiles. Notwithstanding the importance of these results, it is important to note that the Italian labour market is far from uniform across regional, gender, age, and education categories. Therefore, I further contribute to the literature by investigating how an individual's socioeconomic background interacts with demographic characteristics, such as gender and residence, to influence employment opportunities. In an effort to shed light on the demographic disparities in the Italian labour market, this study shows how vulnerable groups - often characterised by women, individuals from the South, and young people - are particularly disadvantaged due to the relevance of an individual's socioeconomic background in their employment condition. Not only does this thesis contribute to the existing bodies of literature on inequality and employment quality, but also offers a new framework for understanding how a person's background and their demographic characteristics interact to influence labour market outcomes.

With a population of roughly 58 million people, Italy is a geographically, socially, and economically diverse country, with sharp differences across groups of individuals. The 2022 Gender Inequality Index reports that Italy scores worse than the European average in all domains except for health. The work indicator of the index, which keeps track of the gap between men and women in the labour market, mostly raises concerns because Italy scores almost 10 points less than the European average. For reference, Germany and Spain perform better than the average, and hence much better than the country under study (EIGE, 2023).

Much attention in the economic development literature has also been devoted

to the North-South divide, which represents a paradigmatic case of within-country development gap (Bigoni et al., 2018). Notwithstanding the "economic miracle" following the Second World War, the sovereign debt crisis and the pandemic crisis have led to an increase in the North-South divergence, with the North covering the majority of domestic production, leading to rising geographical inequalities. Exploring how such divergence affects a person's relative position in the labour market is a relevant object of investigation, given that geographical divergence is not limited to Italy, but can also be found in other countries like the U.S., China, and Germany (Fanti et al., 2023).

Rising concerns are also devoted to the employment opportunities for the young population in Italy. The literature shows plenty of evidence that young Italians are overrepresented among the unemployed (Adda and Trigari, 2016) and that even when employed, they often live in conditions of in-work poverty (Berloffia et al., 2019). Worrying are the increasing numbers of individuals neither in employment nor in education or training (NEETs) overall in Europe, but especially in Italy (Leonardi and Pica, 2013). The causes of this condition are often found in the double-dip recession of recent decades, which has worsened pre-existing structural problems of the labour market, exacerbating contractual conditions and employment opportunities. Many young unemployed individuals, discouraged by the structural problems, end up leaving the labour market and entering the NEET status, which is recognized as a form of social exclusion (Odoardi, 2020).

The literature extensively explores the causes of struggling individuals in Italy with their employment outcomes. Another body of literature also identifies the effects of an individual's background, often measured by parental education, on their employment opportunities. However, little is known about the extent to which demographic conditions, such as gender and geographic residence, interact with an individual's background to influence employment. Furthermore, current research is also limited to the extent that it often does not consider household wealth as a source of status in society, leaving the measurement of an individual's background to their parents' educational attainment.

This study aims to fill these gaps in the literature, by investigating the relationship between an individual's background, measured by parental education and household wealth class, and employment quality in Italy. It also tries to explain how demographic characteristics, such as age, gender, and geographic residence, affect the relationship between background and employment. Focusing on data spanning from 1977 to 2020, this study aims to elucidate the profound impact of wealth inequality and parental education on the employment prospects of the Italian vulnerable groups - including young people, women, individuals from the South, and unskilled workers. By exploring these intersections, this research sheds light on the nuanced challenges faced by such groups in Italy, who often grapple with short-term employment, low wages, and precarious contracts due to a confluence of socioeconomic factors.

To examine the relationship between an individual's socioeconomic background and employment quality in Italy, I deploy a quantile regression model where the de-

pendent variable is the quantile distribution of the net income from labour. Unlike ordinary least squares (OLS) regression, which models the conditional mean of the dependent variable, quantile regression provides insights into different parts of the income distribution, offering a detailed view of how background factors affect various labour income levels. Using historical panel data from the Survey on Household Income and Wealth (SHIW), the analysis includes individual-specific fixed effects to account for unobserved heterogeneity and incorporates interaction terms to explore how socioeconomic background interacts with demographic factors such as gender and geographic residence.

The methodology involves estimating two main equations: the first examines the direct effects of parental education and household wealth on the log of labour income across five quantiles (0.20, 0.40, 0.60, 0.80, and 0.95), and the second investigates the interaction effects between socioeconomic background and demographic variables. The main findings show that an individual's socioeconomic background works well at predicting their employment opportunities. In particular, household wealth class significantly impacts net income from labour, with a diminishing effect at higher quantiles, while parental education notably affects income in the middle to upper percentiles. Older age groups consistently earn higher income, suggesting career progression and experience benefits, whereas young individuals start at lower income levels, making them more vulnerable. Gender disparities are evident, with wealth impacting males more significantly, leading to higher earnings compared to females with similar wealth levels. Regional differences show that individuals in the South experience a stronger impact of household wealth and parental education on labour income, indicating better prospects for those from wealthy and educated families, while Southern females face compounded disadvantages due to a confluence of gender and geographic factors. Lastly, age and education are crucial determinants of labour income, with younger individuals earning less and higher education correlating with increased income, particularly in the upper-income brackets.

To increase the validity of the results and ensure that the findings are not limited to the labour income variable, I explore the relationship between an individual's socioeconomic background and alternative employment quality indicators in the robustness checks. I also use logistic and multinomial logistic regressions to estimate the relationship between an individual's background, measured by household wealth class and parental education, and three employment outcomes indicative of employment quality: employment duration, contract type, and part-time work. This process aims to demonstrate that the evidence from the primary analysis extends to other dimensions of employment quality. The vulnerability and precariousness of the labour market experienced by young individuals, females, and Southern workers are persistent across different employment outcomes, indicating that the log of labour income is a reliable predictor of employment stability in Italy.

The contribution of this thesis to the literature is twofold. Firstly, the literature relies on the measurement of an individual's background through parental education only. I consider a more comprehensive definition of background: I use household wealth class information as an indicator of economic status, and parental education as a measure of social background. Secondly, the literature is currently limited

to exploring the overall effect of background on employment. Even though many authors recognize the importance of age, gender, and education in driving employment opportunities, this thesis is the first effort, to my knowledge, of exploring how background interacts with demographic characteristics to influence employment opportunities, while controlling for age groups and educational attainment. Lastly, I enrich the literature on employment quality by measuring it through four indicators, which rarely appear in research: while the main dependent variable is the labour income distribution, I also use employment duration, part-time work, and contract type in an effort to grasp the stability of a job condition.

The present text is structured as follows. Section 2 describes the Italian context of economic inequality, unemployment, historical background, and labour market institutions. Section 3 presents the literature review of the main theoretical foundations and empirical findings on the relationship between social background and employment opportunities. Sections 4 and 5 describe the dataset at hand and the methodology that I deploy in my analysis. Sections 6 and 7 present the main results from the quantile regression and the robustness checks, and section 8 concludes with some final remarks.

2

Context

The economic and social conditions of many young people in Italy in the last decades have been characterized by rising inequality and precarious employment. Given the evidence at hand and the comparison to other countries in the EU, the Italian case deserves attention on the relationship between socioeconomic background and employment opportunities. This section presents some facts about inequality and unemployment in the country, as well as the historical and institutional contexts.

2.1 Inequality

Amidst decades of economic instability, inequalities in Italy have been on the rise. Using full records of inheritance tax files, Acciari et al. (2021) show that there has been a reversal of fortunes in Italy between the top and the bottom of the distribution since 1995: while top earners have doubled their ability to climb to the top of the income distribution, the bottom 50 percent has been experiencing a secular decline in wealth share. Although wealth concentration appears to be at par with other European countries, the evolution over time shows growing similarity to the U.S. trend (Acciari et al., 2021; Dagnes et al., 2018). Dagnes et al. (2018) confirm the finding of increasing wealth inequality during the past decades in Italy, although it stabilized following the double-dip recession. Brandolini et al. (2018) bring further evidence that income inequality increased steadily since the recession of the 1990s, and less during the double-dip recession, although the share of people in poverty rose sharply. The effects of widening inequality have been a shift of the lower middle class to the low-income class, a widening gap between the wealth of the young and the elderly, and worse living conditions for immigrant households. Acciari et al. (2021) attribute the worsening trend to asset portfolio heterogeneity across the wealth distribution: while poor households hold most of their wealth in savings accounts and valuables, and individuals in the middle of the distribution in the form of real estate, Italians at the top hold financial and business assets, whose recent accumulation was facilitated by the decreasing tax burden.

Lastly, Checchi et al. (2009) contributed to the literature by delving into the evolution of opportunity inequality in the country through the 1990s. The authors find that inequality of opportunity explains roughly 20 percent of overall income inequality in the country, with the South disproportionately affected with respect to the North. The authors exploit a deterministic model, where given circumstances

beyond the control of the individual – parents’ education, race, and gender – any difference in individual income can be attributed to effort. Interestingly, the incidence of inequality of opportunity on overall inequality appears to be highest in the North. The South shows an overall worse situation in terms of opportunity inequality, especially if combined with gender discrimination.

2.2 Unemployment

Youth unemployment in Italy is strictly related to geographical, gender, and education conditions. Using data from the Labour Force Survey from the Italian Statistical Institute (ISTAT), Adda and Trigari (2016) identify the main differences in employment in Italy across different categories. In terms of age, young individuals are overrepresented among the unemployed: between 2012 and 2015, they constituted 25.2 percent of the short-term unemployed and 20.3 of the long-term unemployed. Figure 2.1 displays the unemployment rate trend in the country between 2004 and 2023 for the 15-74 age group compared to the 15-34 one. Although both categories show a decreasing trend in the unemployment rate in the current decade, the young are consistently more unemployed compared to the overall labour force. Leonardi

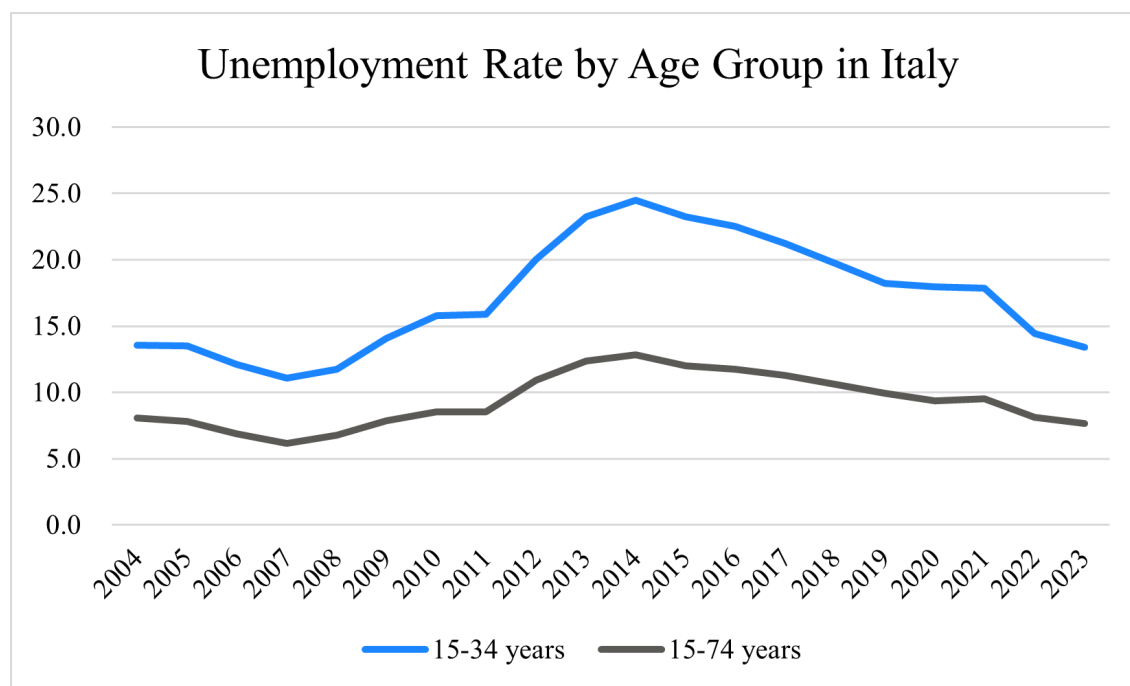


Figure 2.1: Unemployment rate in Italy by Age Group, 2004-2023. Years are reported on the x-axis, while unemployment rates are displayed on the y-axis. Source: ISTAT (2024).

and Pica (2015) report that the high youth unemployment rate in Italy is not new: it has been high since the 1980s and has increased as an effect of the Global Crisis, reaching 40 percent. Even when employed, young people still struggle financially: recent empirical research has forged the term in-work poverty to define the condition where disposable income is not enough to avoid poverty, notwithstanding the employment status. This scenario has become increasingly worrying in Europe, especially in Mediterranean countries (Berloff et al., 2019). Young low-educated people are particularly struggling to find a job and decide to leave the labour force,

ultimately increasing the number of NEETs, who represented 27 percent of the 15-29 age group in 2013 (Leonardi and Pica, 2015).

Looking at the geographical category, the situation tends to be worse in the South, where 29 percent of the Italian labour force lives, but 49.3 percent of it is long-term unemployed. The Global Crisis worsened the conditions in the South where not only was the labour force shrinking, but there were no alternative sectors to rely on, differently from the North (Leonardi and Pica, 2015).

The distribution of unemployment is unbalanced against women, and young women are particularly disadvantaged because they are more likely to be prevalently inactive and experience longer unemployment spells (Berloffia et al., 2019). Although young females are historically associated with higher levels of unemployment, Leonardi and Pica (2015) find that gender differences have been declining since the Global Crisis.

Lastly, looking at the education category, the incidence of unemployment decreases with the level of education, with the population that holds a middle school qualification being overrepresented among the unemployed (Adda and Trigari, 2016). Education is also important to secure job quality and income security since university graduates are more advantaged (Berloffia et al., 2019). However, it appears that unemployment has also increased among graduates (Leonardi and Pica, 2015), and a university degree does not guarantee an advantage in the labour market, given the modest wage premium over high school graduates, and the longer search for the first job (Argentin and Triventi, 2010).

2.3 Historical Background

Following WWII, household disposable income, GDP, and household consumption rose steadily until the currency crisis of 1992. Consequently, household disposable income stopped growing in real terms, although GDP and consumption kept increasing. After years of slow and gradual adjustment to the new standards imposed by the euro, the situation had almost fully recovered in 2007. Following the Global Financial Crisis and the Sovereign Debt Crisis – the double-dip recession – household disposable income fell by 14 percent (Brandolini et al., 2018). As a consequence of the crises, the north-south divide widened, along with intergenerational conflict (Dagnes et al., 2018).

2.4 Labour market institutions

Labour market institutions also play an important role in shaping the occupational outcomes of young individuals in Italy. Until the 1990s, Italy and other Mediterranean countries have often been criticised for having rigid labour markets, where already employed individuals benefit from large social security benefits, leaving new entrants with few choices. Dosi et al. (2018) consider stringent employment protection legislation (EPL) as one of the main causes of the high level of unemployment. To make the labour market more flexible, the Italian government pursued several

reforms. The 1997 “Treu-Package”, the 2003 “Biagi Law”, and the 2016 “Jobs Act” introduced new forms of contracts to which employers could resort, specifically targeting youth unemployment (Cappellari et al., 2012). In addition to the typical contract, with no termination date, high social security contributions, and high firing costs on the one hand, and fixed-term contracts on the other hand, apprenticeships and contractual agreements were introduced and became the main source of temporary employment in the country.

Although empirical research shows that temporary employment helped reduce youth unemployment (Berloffia et al., 2011) and made the Italian labour market more flexible, it remains difficult for temporary employees to transition to permanent contracts, which increases job instability and volatility. In a labour-augmented ‘Schumpeter meeting Keynes (K+S)’ Agent-Based model, Dosi et al. (2018) explore the effects of institutional change on the labour market, and hypothesise that loosening the EPL reduces workers’ bargaining power, while compressed wages lead to higher income inequality, which in turn suppresses aggregate demand and produces further unemployment. Leonardi and Pica (2015) confirm the association between temporary contracts and job insecurity empirically, on the basis that these types of contracts provide low-quality employment standards and uncertainty for prospects for trapped individuals.

There is now a consensus among OECD countries that temporary contracts can have undesirable effects. The concern is that the reforms that took place in Italy are creating a two-tiered labour market. On the one hand, civil servants and holders of permanent contracts are still heavily protected; on the other hand, holders of apprenticeships, short-term contracts, temporary jobs, and self-employment, are left with fewer rights and low wage growth opportunities (Barbieri, 2009). Under the current system and following the abrupt changes in the labour market of recent decades, females, new entry cohorts, and unskilled workers in Italy face precarious employment, which increases unemployment risk over time as well as poverty traps.

3

Literature

This section outlines, compares and discusses the key theoretical models and empirical findings that shape the relationship between an individual’s background and their employment opportunities. I first present the theoretical foundations on the matter, and then the empirical evidence from Italy and other countries in Europe. This section serves as a motivation for the study and to shape the main hypotheses.

3.1 Theoretical Foundations

Theoretical attempts to explain the dramatic scenario of youth unemployment in Italy are limited but effective. They have considered social background and institutions as the main drivers. D’Agostino and Regoli (2012) build a life course causal model to explain how monetary poverty, measured by disposable income, and deprivation poverty, measured by consumer durables, amenities, financial situation, and environment, are affected by family background, either directly or indirectly through education. The main assumption is that social origin is important for people to achieve high socioeconomic status, and social class is systematically correlated with mortality, health, job opportunities, and educational attainment (Dagnes et al., 2018). Parents influence their children’s life chances by investing in education, which in turn is relevant to their occupational status. The authors find that “teenage poverty” reaches 30 percent in Italy. Consequently, in a context where education is mainly financed privately, their probability of receiving tertiary education decreases, with worsening prospects for future employment stability.

Calvó-Armengol and Jackson (2006) provide an alternative theoretical model to explain how social background, defined by social networks rather than family socioeconomic status, affects employment and inequality. In their simple model of transmission of job information, an agent randomly receives information about jobs and decides whether to switch jobs or pass the information to someone unemployed. This creates networks where, if everyone starts with a good employment status, individuals in that group are less likely to drop out of the labour market. Not only does this model demonstrate the importance of an individual’s status in labour markets, but also hints at a positive correlation of employment across time and agents. As individuals grow older and make meaningful network decisions, their employment status improves, which could explain the precariousness of employment conditions for the young.

Building upon these theories, my empirical model seeks to explore how an individual's socioeconomic background, encompassing factors such as family wealth and parental education, interacts with employment outcomes in Italy. Drawing from the insights of D'Agostino and Regoli (2012), I investigate the extent to which family background influences occupational conditions while recognising the role of and controlling for educational attainment. While my study does not directly address the role of social networks and information transmission as proposed by Calvó-Armengol and Jackson (2006), I recognise the broader implications of social connections in shaping employment opportunities. I also use wealth class as an indicator of the type of networks a worker is most likely to relate to, and hence shape employment opportunities.

3.2 Empirical Research

Empirically, the attention on the topic has mostly been concerned with the question of how family background as a source of an individual's status affects occupational outcomes. Argentin and Triverti (2010) find that parents' education is positively correlated with the probability of entering higher education, which helps reduce job instability. They hypothesise that the inheritance of a family business and the higher social capital, which comes with parents' education, increase the probability for an individual to achieve successful labour market results. Berloffia et al. (2011) use the Italian Households Longitudinal Study (Ilfi) over the 1990s and 2000s to explore – with a multinomial logit by education cohort – two main channels that explain how individuals from higher social classes have a higher probability of achieving secure employment rather than insecure employment or unemployment: a social channel, proxied by father's occupation, and a cultural channel, proxied by mother's education, which is famously correlated with children's cognitive and non-cognitive skills. The authors find that individuals in the upper-class and white-collar children do have an advantage in the labour market, in terms of status, income, and correspondence between university degree and job performed.

Once assured of the relationship between social class and labour market performance, the literature also looks at the dynamic interplay between social status and gender. McGinn and Oh (2017) report that women's employment opportunities and behaviour are often influenced by both social background and gender ideologies. The paper is also influential in describing what constitutes social class: at the household level, class is determined by overall wealth and income, while at the individual level own and parents' income, education, and occupation matter. However, the discussion of the interplay between socioeconomic background and gender as related to employment opportunities remains limited, and this thesis aims to shed more light on this topic.

As an additional source of motivation for this study, it is interesting to observe how the ongoing literature in Italy is located in the more general European context. Harrison and Rose (2006) built the European Socio-economic Classification (ESeC), an indicator of social background that considers market position and occupation as the main drivers of the stratification system. The indicator considers whether the in-

dividual is self-employed, has an occupation based on a service relationship, a labour contract, or a mixed-form contract. Lucchini and Schizzerotto (2010) conducted a study to explore whether the ESeC Schema is a valid predictor of employment opportunities for individuals in Europe, hypothesizing that an individual is more likely to become unemployed as they move from self-employment to labour contract. They also assume that the higher the required level of skills to perform an occupation, the lower the chances of losing their job. By focusing on a comparison between Austria, Denmark, Italy, and the UK from the 1990s to the first years of the current century, the authors find that current occupation is a valid predictor of social background, and self-employed workers face lower risks of unemployment in all countries than all other categories. They also confirm the prediction that labour contract workers are the ones who are most likely to experience unemployment.

Research shows that the Italian case of socioeconomic background as a predictor of education and work career is not isolated in Europe. Studying three birth cohorts born in the middle of the 1970s in Sweden, Berggren (2013) finds that gender, social background, and immigration affect the success of individuals in the labour market. Although women perform better than men in the Swedish educational system, the same is not true in the labour market. And the social background, proxied again by parental education, directly affects children's success by influencing their interest, motivation and choices. Not only do students with highly educated parents have double the probability of completing high school, but they also get jobs with post-secondary education requirements. Although men and women are equally likely to hold high-profile employment opportunities if they get tertiary education, men are facilitated by their easier access to networks.

Broader cross-country studies on the effect of social background on youth employment in Europe have concluded that social background influences job opportunities through a direct and an indirect channel (Iannelli and Smyth, 2008). The former acts through parents' cultural capital, while the latter through education. The authors find that European countries differ in the extent to which education mediates the relationship between social background and labour market performance. In countries that adopt a conservative or familial welfare system – Belgium, France, Italy, Spain, and Greece in the study – almost all the differences in employment opportunities can be explained by differences in education. Access to paid employment is also dependent on gender: women are mostly disadvantaged in conservative and familial welfare regimes, while the gender gap is narrower among Nordic and Eastern European countries (Iannelli and Smyth, 2008).

Naswall and De Witte (2003) add to the discussion an important analytical feature. They consider the effect of demographic variables such as age and gender as well as social background on job insecurity. The authors' choice of exploring the influence of socioeconomic background on job insecurity is pivotal for this thesis. My study analyses a broad range of employment outcomes, including stability and financial status, to appreciate a deeper understanding of the conditions of employment. The authors define job insecurity as the subjective perception that an individual finds themselves in the position to leave their job sooner than expected. Such insecurity changes across employment dimensions and countries. For exam-

ple, different categories of gender, age, and social status have different perceptions of job insecurity: workers holding positions with more or less stringent education requirements, holders of part-time or full-time positions, and contingent vis-a-vis permanent workers are all expected to have different insecurity perceptions. The results highlight that different dimensions matter more in some countries than in others. For instance, women, unskilled workers, part-time, and contingent workers show higher employment insecurity. Gender does not constitute an issue in the Netherlands and in Sweden, where job insecurity is mostly related to employment contingency. Age and social status play a relevant role in Belgium, Italy, and Sweden, although they don't in the Netherlands.

In conclusion, the discussion highlights the importance of exploring the Italian case within the broader European context, particularly concerning the influence of an individual's background and gender on labour market outcomes. Social background, often proxied by parental education, exerts a significant influence on individuals' career trajectories in the country, and research shows an intricate interplay between gender and social background. Studying the Italian case, where the impact of social background and its relation to gender is probably magnified, offers valuable insights into the broader dynamics shaping youth employment in Europe.

3.3 Hypotheses

Drawing on this section's theoretical and empirical conclusions, it is reasonable to expect a few hypotheses. The first prediction is based on the theoretical model by D'Agostino and Regoli (2012), which identifies that teenagers who live in poverty are less likely to receive adequate education and hence achieve better employment opportunities. Therefore, I expect that:

- **Hypothesis 1.** As we move along the household wealth class distribution, workers enjoy better employment conditions, other things being equal.

Based on the theoretical and empirical findings by D'Agostino and Regoli (2012), Argentin and Triverti (2010), and Berloff et al.(2011), the second hypothesis states that:

- **Hypothesis 2.** As the parental education of individuals improves, their labour market outcomes also improve.

Based on the findings by McGinn and Oh (2017), which find that women's employment opportunities are dictated by background and gender ideologies, the third hypothesis advocates the following:

- **Hypothesis 3.** The interaction between gender and an individual's background, defined by wealth class and parental education, should yield that female workers from lower backgrounds are significantly disadvantaged in the labour market vis-a-vis male workers.

Based on the contextual evidence of the important regional divide in Italy (Leonardi and Pica, 2015; Dagnes et al., 2018), it is likely that workers who reside in the South are vulnerable to the disadvantages of the labour market:

- **Hypothesis 4.** The interaction between an individual's geographic residence and their background defined by wealth class and parental education should yield that Southern workers from a lower socioeconomic status are significantly disadvantaged in the labour market compared to their Northern counterparts.

Lastly, with regard to the contextual and empirical evidence of the disadvantage suffered by the young population in the country (Berloffia et al., 2019; Leonardi and Pica, 2015), I expect as follows:

- **Hypothesis 5.** Different age groups are likely to experience varying employment conditions. Young people are more likely to have a disadvantage than older generations.

4

Data

This section describes the dataset I use to analyze the relationship between an individual's socioeconomic background and employment opportunities in Italy and presents the summary statistics of my observations. I describe the data source first, then present the main variables of interest with their statistics.

4.1 Source Material

I take the data from the Survey on Household Income and Wealth (SHIW) that the Bank of Italy has collected every two years since the mid-1960s. The survey collects data on the wealth, economic, and financial behaviour of about 7000 Italian households and 16000 individuals. I use the publicly available historical archive which includes waves from 1977 to 2020. The archive offers individual-level information regarding age, gender, and education attainment, household-level data on wealth and parental education, as well as the occupational status of individuals, their income from dependent work, and various information on their employment conditions.

In terms of comparability throughout the years, the archive only includes the variables that are homogeneous across the waves. The dataset is divided into different data files based on the category of the variables of interest. I use datasets on wealth, income, general, and employment information. The level of analysis changes through the different datasets: while employment and general information is available at the individual and household levels, wealth information is only available at the household level. Although some households and individuals change through the waves, it is easy to identify households that have been repeatedly surveyed over the years. The comparability of the outcomes for the same observations is therefore achievable by merging the data files and only considering the repeated observations through the years.

The Bank of Italy warns of potential measurement errors in the data collection process, due to response bias or coding errors. The organization suggests that in the absence of a Computer-Assisted Personal Interviewing (CAPI) survey, the elimination or the drastic reduction of measurement error is almost impossible. While it is essential to acknowledge the potential for measurement error in the data collection process, it is also important to note the measures undertaken to mitigate such concerns. Specifically, thousands of control phone calls are conducted for each wave of

data collection, ensuring the accuracy and reliability of the data interpretation. By implementing these rigorous quality control measures, this study aims to minimize the impact of measurement error and uphold the integrity of the findings.

A second relevant concern relates to the measurement of household wealth with the current dataset. While Acciari et al. (2021) choose to work on inheritance tax files, most of the authors rely on the readily available and easy-to-use SHIW. However, the present survey has been criticized for not fully capturing the wealth holdings at the top mostly because of under-reporting and tax avoidance strategies. This is particularly relevant in the Italian context where, as Checchi et al. (2018) state, labour uncertainty has reduced the power of income to predict living conditions, and households resort to their wealth as sustainment. Despite the validity of the criticism, it's also important to acknowledge the advantages offered by the survey dataset. Notably, its user-friendliness, consistency across time and space, and minimal degree of measurement error make it a valuable resource for research purposes. To my knowledge, it is the only Italian survey linking households and individuals across different waves on so much information.

Moreover, this thesis adopts a comprehensive approach by considering various facets of individuals' socioeconomic backgrounds: the economic dimension, as reflected by wealth inequality, and the social dimension, measured by parental education. While I acknowledge that the wealth-based inequality distribution may suffer from under-reporting at the top of the wealth distribution, it remains a reliable tool for capturing discernible effects. If anything, when interpreting the results it is important to consider that any identified effects are likely to be even more pronounced in reality. Additionally, the inclusion of parental education as a proxy for social background offers a nuanced perspective that may help mitigate the under-reporting of wealth information.

4.2 Variables and Statistics

This section aims to broadly describe the identity of the whole sample under study. I first describe the main variables of interest, as available in the SHIW, and then present their summary statistics. Although not all variables have available data across all waves, this section aims to present all available information, with the purpose of identifying a suitable methodology. To further elucidate the characteristics of the sample, I also include in this section the statistics of the variables as reported in Table 4.1.

The general household and individual-level information available in the SHIW includes several variables of interest for the analysis. At the individual level, information is provided on gender, age, education level, and region of residence. All variables are available for all waves. Since the 1993 survey year, the dataset has also included parental educational attainment, which has traditionally been used to measure an individual's social background. As reported in Table 4.1, the dataset divides the sample into different age groups: up to 30, from 31 to 40, from 41 to 50, from 51 to 65, and over 65. This categorization is important because the reference category of my study is young people. The most frequent age group is the 51-65 one

while the least frequent is the 0-30 age group. It is also important to specify that over 90 percent of the young age category is 19 years old or older.

Table 4.1 shows that the sample records more information on male participants than female ones. The survey records double the size of information in the North compared to the South due to the fact that a larger proportion of Italians live in the North. While 8 percent of the population does not hold any level of education, a negligible proportion holds a post-graduate degree. However, at least 80 percent of the population holds a primary, middle, or high school diploma. Lastly, the parental education variables also display interesting, although not surprising, preliminary information: the largest proportion of parents who do not hold any type of education is female, and the number of fathers who pursued a post-graduate program is three times the number of mothers. On average, mothers' education is mostly concentrated around primary and middle school, while fathers' education is more distributed across the different education categories.

In my analysis, I measure an individual's economic status by using household-level wealth information. This category in the SHIW includes household-level net wealth (available from 1991), which is the result of the addition of real assets - real estate, businesses, and valuable items (available for all waves) - and financial assets - deposits, government securities, and credits (available from 1987). The SHIW also provides a family wealth class available from 1991, which categorizes households across 10 classes based on net wealth deciles. Table 4.1 reports the summary statistics and frequency of the wealth class deciles. The average income is found at the 6th decile, and the number of people in each decile increases as we move along the wealth distribution. The information on wealth is important because one of the main contributions of my analysis is a more comprehensive measurement of an individual's background, by including both wealth information and parental education to capture the effect of social and economic status on the net earnings from labour and other employment outcomes.

Employment-related data can generally be categorized into two groups: the one that quantitatively assesses the quantity of employment in a country - such as the unemployment level and rate -, and the one that considers the quality dimension of employment. The latter reflects the ability of employment to provide not only financial security but also stability, opportunities for advancement, and a sense of job satisfaction and fulfillment for the worker. This thesis focuses on the quality dimension of employment because of its relevance in the current literature. As the main outcome of my analysis, I consider the distribution in quantiles of the log of labour income, after taxes and contributions. I include in Table 4.1 the summary statistics of the log of net labour income, with an average of 9.01 compared to the maximum of 13.12.

Notwithstanding the importance of the net labour income variable in measuring the financial benefit from any employment condition, other individual-level employment information is useful to provide alternative indicators of employment quality and test the robustness of my findings. In the robustness checks, I perform the analysis with other outcomes that help integrate the different aspects of employment

Table 4.1: Summary Statistics of General Information and Employment Outcomes

	Mean	St. Dev.	Min	Max	N	Frequency
General Information						
Age Group	3.31	1.39	1	5	279,082	1
Up to 30					42,029	0.15
31-40					43,677	0.16
41-50					50,052	0.18
51-65					73,572	0.26
65+					69,752	0.25
Gender	0.72	0.50	0	1	279,082	1
Male					157,445	0.56
Female					121,637	0.44
Geographic Area	0.33	0.47	0	1	279,082	1
North					188,363	0.67
South					90,719	0.33
Education	3.01	1.12	1	6	279,037	1
None					23,007	0.08
Primary School					75,398	0.27
Middle School					83,949	0.30
High School					69,449	0.25
Graduate					25,952	0.09
Post-Graduate					1,282	0.00
Father's Education	2.61	1.75	1	7	172,169	1
None					41,401	0.24
Primary School					76,423	0.44
Middle School					20,311	0.12
High School					11,796	0.07
Graduate					4,578	0.03
Post-Graduate					107	0.00
Don't know					17,553	0.10
Mother's Education	2.44	1.70	1	7	172,169	1
None					48,782	0.28
Primary School					78,537	0.46
Middle School					16,715	0.10
High School					9,798	0.06
Graduate					1,870	0.01
Post-Graduate					29	0.00
Don't know					16,438	0.10

	Mean	St. Dev.	Min	Max	N	Frequency
Household Wealth Class	6.05	2.86	1	10	188,697	1
1st decile					14,612	0.08
2nd decile					14,510	0.08
3rd decile					15,572	0.08
4th decile					15,745	0.08
5th decile					17,943	0.10
6th decile					19,242	0.10
7th decile					20,636	0.11
8th decile					21,702	0.12
9th decile					23,027	0.12
10th decile					25,708	0.14
Employment Outcomes						
Log Labour Income	9.01	0.87	2.33	13.12	129,991	1
Employment Duration	0.88	0.97	0	1	128,711	1
Part of year					15,185	0.12
Whole year					113,526	0.88
Type of Contract	1.16	0.41	1	3	550,91	1
Permanent					46,901	0.85
Fixed-Term					7,386	0.13
Temporary					804	0.01
Part-time Work	0.10	0.30	0	1	101,575	1
No					91,412	0.90
Yes					10,163	0.10

stability: contract type, which takes different values if the individual is employed with a permanent, fixed-term, or temporary contract; the duration of the main professional activity, available as a binary variable that takes the value of 0 if a worker was employed for part of the year and 1 if a worker was employed for the entire year; a part-time work variable, which takes the value of 1 if a person has a part-time occupation and 0 otherwise. All variables are available for all waves except for contract type, which is only available from the 2002 survey year. Table 4.1 reports that almost 90 percent of the sample works through the entire year. Furthermore, the vast majority of the population holds a permanent contract (85 percent), compared to 1 percent holding a temporary one, and does not work part-time (90 percent).

4.3 Employment Statistics by Gender, Geography, and Year

This paragraph aims to visually explore how the distribution of labour income, as well as the proportions of employment duration, part-time work, and contract type, differ through gender, geographic residence, and year. This preliminary analysis is important because it vividly shows that different demographic categories are related to employment outcomes differently. Firstly, Figure 4.1 reports the distribution of

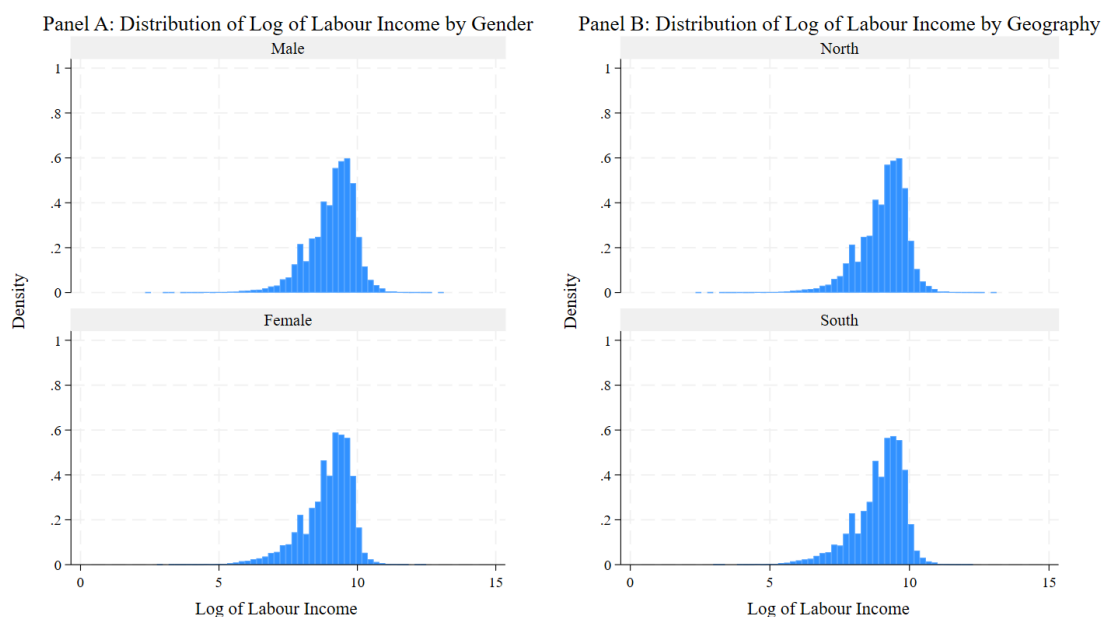


Figure 4.1: Distribution of Log of Labour Income by Gender and Geography. Panel A shows the distribution of the log of labour income by gender, with the male distribution at the top and the female distribution at the bottom. Panel B shows the distribution of the log of labour income by geographic residence, with the North distribution at the top and the South distribution at the bottom. The y-axis reports the distribution density, and the x-axis reports the log of labour income.

the log of labour income by gender and geographic residence. As Panels A and B respectively show, the distribution of earnings has longer tails and shows a higher median for male workers and Northern workers with respect to their female and



Figure 4.2: *Distribution of Log of Labour Income by Year.* The graph reports the distribution of the log of labour income for the whole sample throughout the panel from 1977 to 2020. The y-axis reports the distribution densities for every year, while the x-axis reports the log of labour income.

Southern counterparts. Since the labour earnings variable has been available since the first wave of the historical archive of the SHIW, Figure 4.2 depicts how the distribution of earnings in Italy changed from 1977 through 2020. Although the general trend shows an overall improvement, the population has witnessed stagnant growth in the last 15 years. This preliminary analysis shows that there is reason to believe that female and Southern Italians find themselves in a disadvantaged position in the labour market, as long as labour income is concerned.

Figures 4.3 and 4.4 show the proportions of employment duration by gender and geographic residence ¹. Female workers are consistently less occupied throughout the whole year than their male counterparts. The same holds for Southern workers compared to Northern. Again, this is evidence that employment conditions are less stable for women and Southern people in Italy.

Figures 4.5 and 4.6 show the proportions of part-time workers by gender and geographic residence ². In this case, the pattern observed in the previous variables, which associates female workers with Southern workers as disadvantaged groups, is not repeated: while women consistently show a much larger proportion of part-time

¹The yearly proportions of the remaining employment variables are included in the Appendix. Figure A.1 shows that, since the beginning of the 2000s, which coincides with the first labour market reforms in Italy, the proportion of people working through the entire year has progressively diminished, possibly as an effect of the labour market reforms of those years.

²Figure A.2 illustrates that ever since the part-time work variable was introduced into the SHIW in 1986, holding a part-time position has become more and more common, with the exception of 2016 and 2020. This could be explained by the fact that recent institutional arrangements have increased the availability of jobs, but not necessarily improved their conditions.

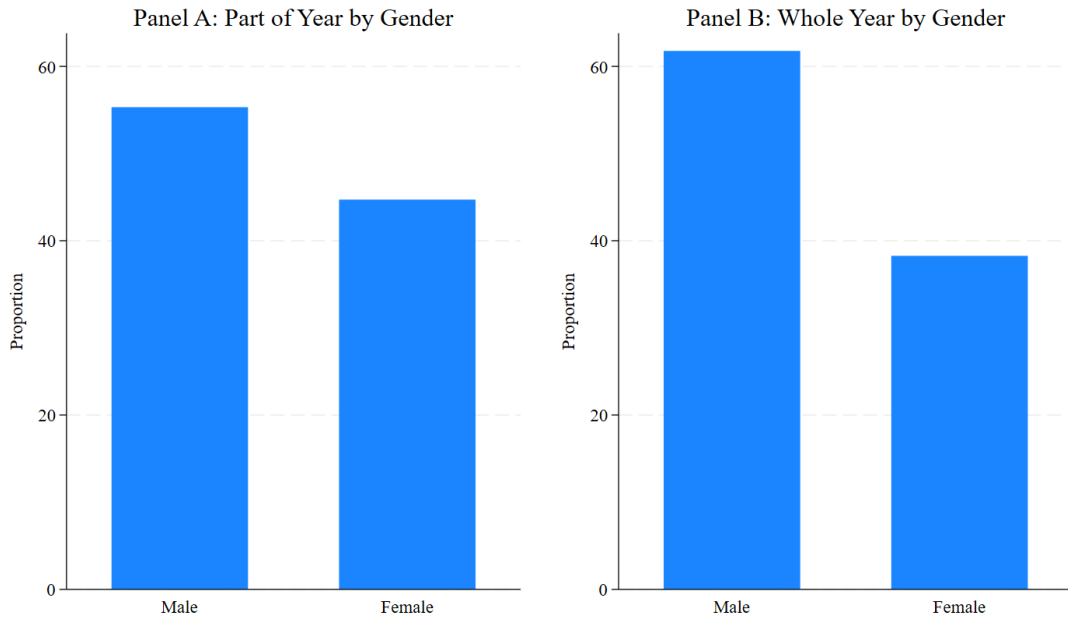


Figure 4.3: Proportions of Employment Duration by Gender. Panel A provides the proportions for the part of the year category of duration, while Panel B provides the proportions for the whole year category. The y-axis reports the proportions of employment duration as percentages (out of 100), while the x-axis reports the gender categories.

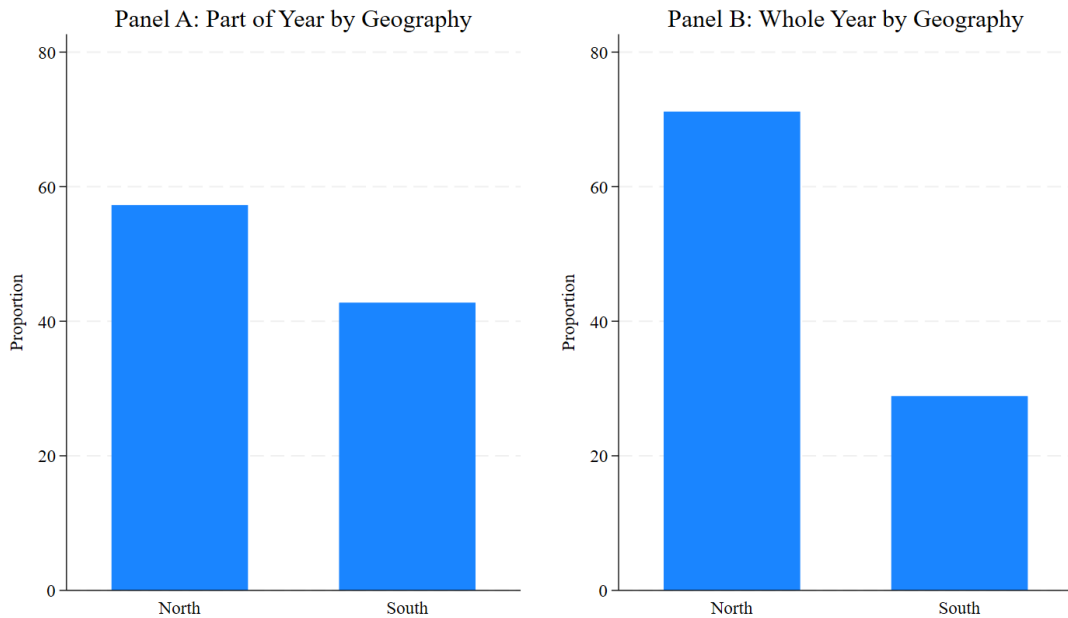


Figure 4.4: Proportions of Employment Duration by Geography. Panel A provides the proportions for the part of the year category of duration, while Panel B provides the proportions for the whole year category. The y-axis reports the proportions of employment duration as percentages (out of 100), while the x-axis reports the geographic categories.

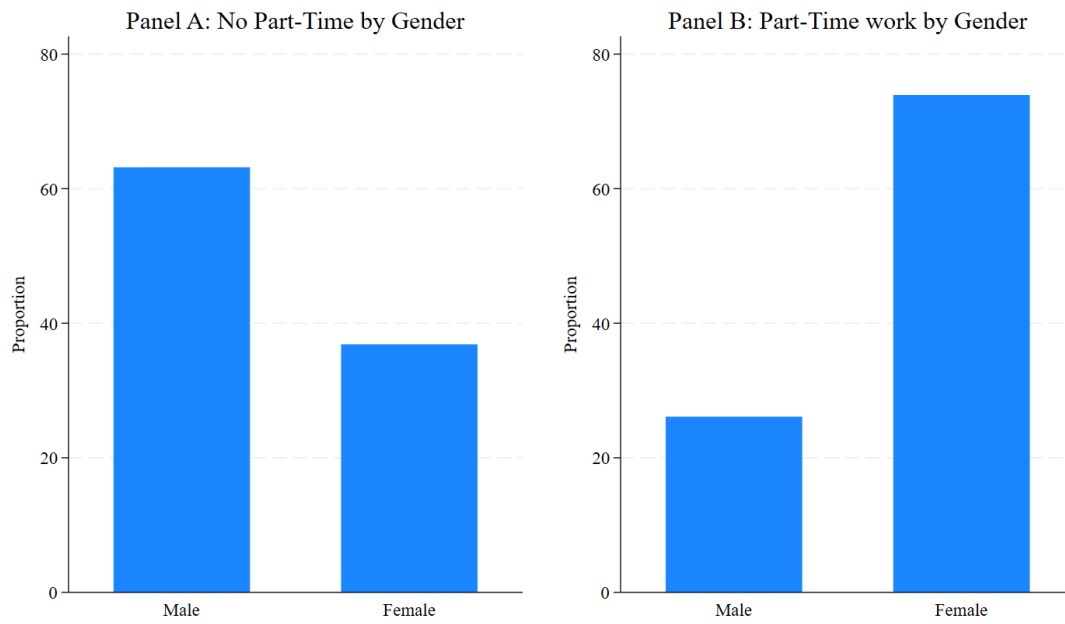


Figure 4.5: Proportions of Part-Time work by Gender. Panel A provides the proportions for the no part-time category of part-time work, while Panel B provides the proportions for the part-time category. The y-axis reports the proportions of part-time work as percentages (out of 100), while the x-axis reports the gender categories.

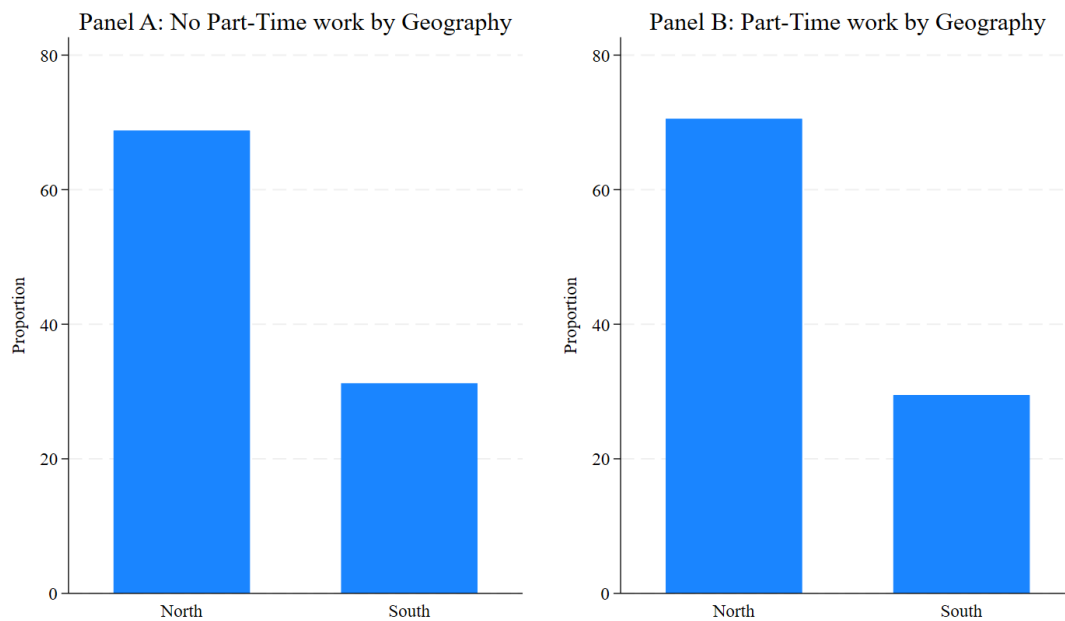


Figure 4.6: Proportions of Part-Time work by Geography. Panel A provides the proportions for the no part-time category of part-time work, while Panel B provides the proportions for the part-time category. The y-axis reports the proportions of part-time work as percentages (out of 100), while the x-axis reports the geographic categories.

work compared to men, part-time work is mostly concentrated in the North. This picture shows that, although the part-time variable conveys important information about the extent to which an individual holds a precarious employment position, it can also be explained by many different variables other than demographic origin or labour market disadvantage. For instance, it is possible that female workers hold more part-time positions than men to take care of the family or children, which would confirm the disadvantaged position of women in the labour market in Italy. However, according to the precariousness of labour hypothesis, disadvantaged groups - including Southern people - should more likely suffer from the low availability of employment opportunities, which would lead people to hold part-time positions in the absence of full-time ones. Further research could investigate on a deeper level the determinants of holding a part-time position in the South with respect to the North of the country.

Lastly, Figures 4.7 and 4.8 clearly show that women are less likely than men to hold permanent positions, while the proportion of women holding a fixed-term contract increases with respect to female workers holding a permanent one. The same holds for Southern workers, again confirming the similar pattern previously discussed ³.

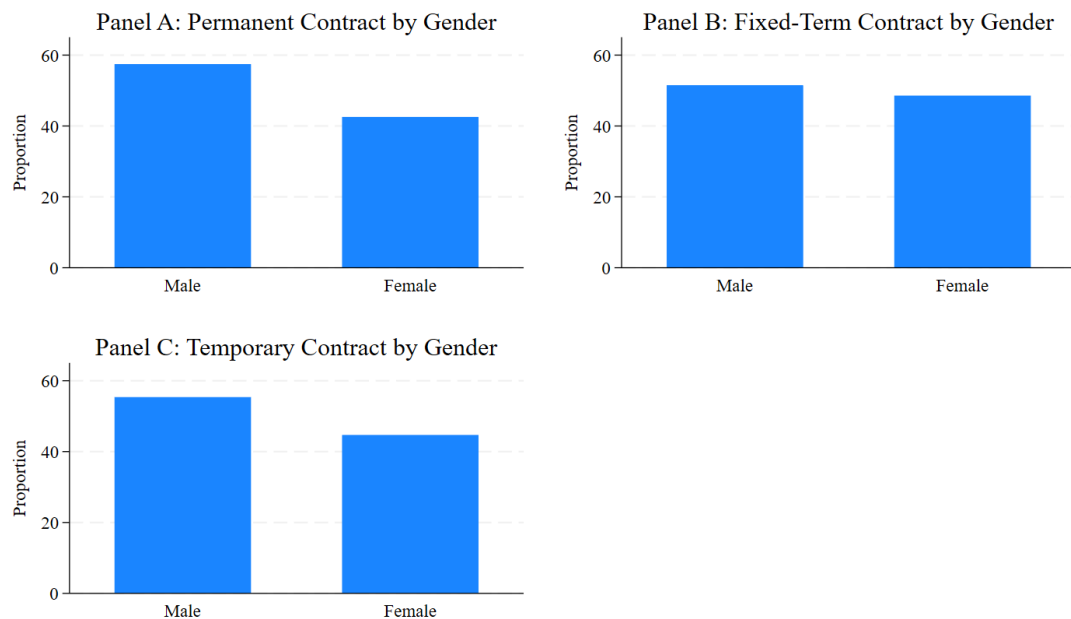


Figure 4.7: Proportions of Contract Type by Gender. Each panel provides the proportions of male and female workers by a particular contract type. The y-axis reports the proportions of a contract type holders as percentages (out of 100), and the x-axis reports the gender categories.

³Figure A.3 illustrates that, since the introduction of temporary contracts, their use has been on the rise in the country, at the expense of permanent and fixed-term contracts. However, it is not possible to test whether the decreasing trend was present in the previous century because the contract type variable was only introduced in the 2000 round.

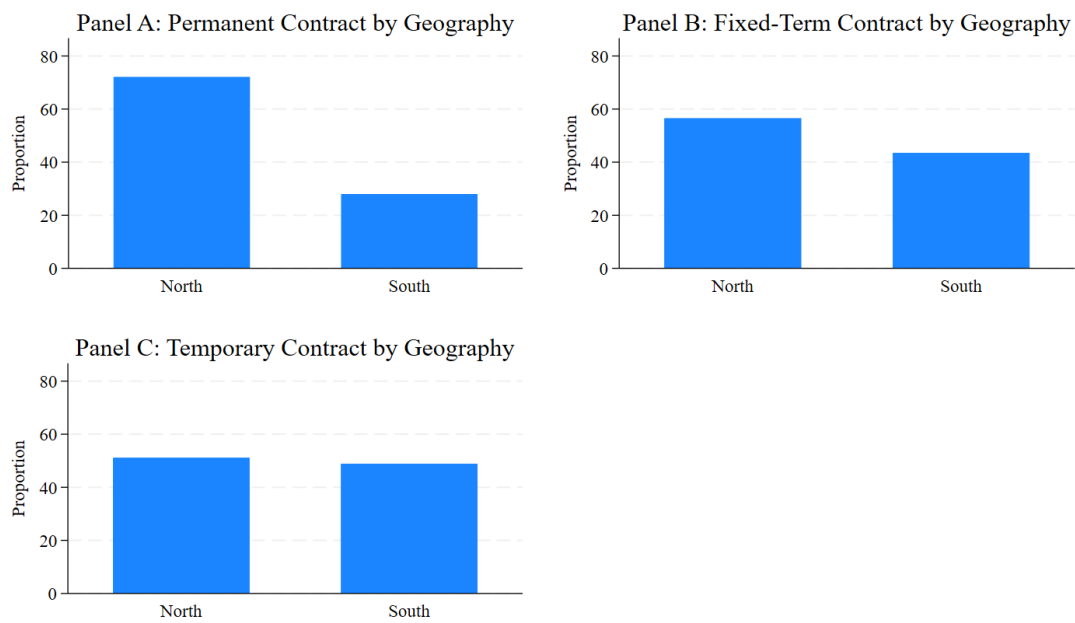


Figure 4.8: Proportions of Contract Type by Geography. Each panel provides the proportions of male and female workers by a particular contract type. The y-axis reports the proportions of a contract type holders as percentages (out of 100), and the x-axis reports the geographic categories.

5

Methodology

In this section, I describe the quantile regression model, which I deploy to investigate the intricate relationship between an individual's background and the main employment outcome - the log of net labour income. Unlike OLS, quantile regression models different parts of the distribution, such as the quantiles, other than modelling the conditional mean of the dependent variable. By deploying individual-specific fixed effects to account for unobserved heterogeneity and incorporating interaction terms, the model offers insights into how an individual's background interacts with demographic factors, such as gender and geography, to shape the labour earnings distribution. The first paragraph deals with the theoretical framework of quantile regression, mainly based on the article by Rios-Avila and Maroto (2022). The second paragraph explains in greater detail the empirical application of quantile regression in the context of my analysis. It also describes the role and constitution of the outcome, independent, and control variables.

5.1 Theoretical Framework of Quantile Regression

The main method of my methodology is a quantile regression model with individual-level fixed effects. Quantile regression is used to estimate the relationship between the independent variables and a quantile of the dependent variable's distribution. This method provides a more comprehensive understanding of how an independent variable affects different segments of the dependent variable's distribution, capturing the variability that might not be captured by mean-based OLS regressions (Rios-Avila and Maroto, 2022). There is reason to believe that the relationship between social and economic background and labour earnings changes across the distribution, and that particular demographic groups are more disadvantaged than others, as hypothesised in Section 3.3.

Notwithstanding the extraordinary ability of linear regression analysis to provide the best unbiased estimate estimator for the expected change in an outcome variable, associated with a one-unit increase in the independent variable, *ceteris paribus*, this model often fails to provide the best estimator in a setting where homoscedasticity and normality do not hold. In particular, the distribution of earnings is often skewed and has many outliers. On the other hand, conditional quantile regression makes it

possible to identify heterogeneous effects by quantifying changes in the distribution of a continuous variable among individuals with different characteristics (Rios-Avila and Maroto, 2022). For example, I can examine how an additional year of parental education affects the conditional distribution of earnings for workers with specific observed characteristics.

Rios-Avila and Maroto (2022) also discuss the interpretation of a conditional quantile regression model. Such interpretation answers the following question: how much would the earnings distribution change if every individual with specific observed characteristics belonged to a higher wealth decile, or if their parents achieved a higher educational attainment level? It follows that the quantile regression coefficients do not directly apply to individual predictions because we do not know an individual's specific position in the conditional distribution. Instead, we interpret the same quantile across different conditional distributions or assume that a person remains in the same ranking, after their characteristics change. Given that the coefficients indicate how changes in the independent variable affect the conditional quantiles of the dependent variable, the interpretation of quantile regression coefficients does not change whether the explanatory variable is continuous or discrete. Because the effects of explanatory variables depend on the conditioning characteristics, it is common to estimate and interpret these effects for an average individual (i.e., at mean characteristics).

I can use this method to quantify the changes in the conditional distribution of earnings, measured in quantile differences, associated with different levels of parental education, household wealth class, and other relevant variables. This allows me to compare the effects across different quantiles and assess whether the influence of social background varies at different points of the income distribution. Using this method is particularly relevant in the context of my research question, because of two main reasons. Firstly, by looking at the preliminary illustrations of the dataset, the log of net labour earnings variable is highly skewed and includes many outliers. In this case, a linear regression model would fail to address its main assumptions. Secondly, my research question entails observing the distribution of income, rather than the average income, to see what strata of society are relatively disadvantaged with respect to others.

5.2 Empirical Application of Quantile Regression

To answer my research question, I apply the conditional quantile regression method and divide the log of labour income distribution into five quantiles ¹. The aim is to explore the effect of social background on earnings at the 20th, 40th, 60th, 80th, and 95th percentiles of the distribution. The first equation that I estimate in my

¹Three key assumptions of the quantile regression model - the linearity of predictors, the absence of multicollinearity, and homoscedasticity - were tested to ensure unbiased estimators. The Appendix shows the graphical illustrations for the assumptions. The scatterplots in Figures A.4 and A.5 explore and ensure the linearity of predictors. The scatterplot of residuals against predicted values in Figure A.6 brings evidence in favour of homoscedasticity in the data. The correlation matrix in Table A.1 shows no sign of multicollinearity among the explanatory variables.

empirical strategy is the following:

$$\begin{aligned} \text{Log(Labour Income)}_{it} = & \alpha + \beta_{q1} \text{Wealth Class}_{it} \\ & + \beta_{q2} \text{Parental Education}_{it} + \beta_{q3} \text{Age Group}_{it} \end{aligned} \quad (5.1)$$

where α accounts for individual fixed effects, i stands for individual $i = 1, 2, \dots, n$ and t is a suffix for the year variable. The first equation explores the relationship between an individual's background, captured by the variables *WealthClass* and *ParentalEducation*, and their earnings, described by the dependent variable *LogofLabourIncome*. β_q is the vector of unknown parameters related to the q^{th} quantile.

The second equation that I estimate in the empirical analysis is focused on the interaction between social and economic background and demographic characteristics - i.e., gender and area of residence - and its effect on the log of labour income:

$$\begin{aligned} \text{Log(Labour Income)}_{it} = & \alpha + \beta_{q1} \text{Wealth Class} * \text{Female}_{it} + \beta_{q2} \text{Wealth Class} * \text{South}_{it} \\ & + \beta_{q3} \text{Parental Education} * \text{Female}_{it} + \beta_{q4} \text{Parental Education} * \text{South}_{it} + \beta_{q5} X_{it} \end{aligned} \quad (5.2)$$

Again, α accounts for individual fixed effects, i stands for individual $i = 1, 2, \dots, n$, and t is a suffix for the year variable. In the empirical analysis, I always control for individual-level fixed effects - α - and age group - included among the X controls. I also include a specification in which I control for the level of education ².

After exploring the relationship between an individual's social and economic background and the earnings distribution, it is interesting to explore how this relationship is affected by gender - included in the interaction terms *Wealth Class * Female* and *Parental Education * Female* - and geography - included in the interaction terms *Wealth Class * South* and *Parental Education * South*. Each interaction variable combines the effect of a demographic factor, whether it be gender - 0 for male; 1 for female -, or of the geographic dummy - 0 for North; 1 for South - with household wealth class in deciles, or with the parental education index. For instance, a significant coefficient for the *Wealth Class * Female* interaction suggests that the relationship between wealth class and the log of labour income varies by gender. If the coefficient is positive, it indicates that the association between wealth class and income distribution is stronger for females compared to males. Likewise, a significant coefficient for the *Parental Education * South* suggests that the relationship between parental education and the log of labour income varies for individuals residing in the South of Italy. A positive coefficient would then imply that the educational attainment of the parents in the South of the country, on average, is more relevant in determining the income distribution quantile than it is for people from the North.

In particular, the β_1 coefficient represents the change in the q^{th} quantile of the log of labour income associated with a one-unit change in wealth for females compared to males. Likewise, the β_2 coefficient indicates how the effect of wealth on labour

²In earlier analyses, I also controlled for marital status. However, I do not include it here because the variable does not affect the results, and the coefficients for marital status categories are non-significant.

income varies between individuals in the South and the North at the q^{th} quantile of the income distribution. The same logic applies to the parental education interaction terms: while β_3 represents the change in the q^{th} quantile of the log of labour income associated with a one-unit change in parental education for females compared to males, the β_4 shows how the effect of parental education on labour income varies between individuals in the South and the North at the q^{th} quantile.

The remaining paragraphs explain the nature and construction of the outcome, explanatory, and control variables.

5.2.1 Outcome variable: Log of Labour Income

Since this thesis aims to explore the relationship between an individual's socioeconomic background and employment quality in Italy, and how this relationship changes across different demographic categories, particular attention was devoted to the selection of the main dependent variable. It has already been mentioned that the debate on employment opportunities for young people is centred around two pillars: quantity and quality of employment (Berloffia et al., 2011; Leonardi and Pica, 2015; D'Agostino and Regoli, 2012). The quantity dimension of employment can be computed through unemployment counts and rates. On the other hand, in my analysis, employment quality comprehensively encompasses different aspects of a job position, considering factors such as the duration of the activity, the stability and consistency of earnings, the nature of employment (part-time vs full-time), and the type of contract, distinguishing between permanent, fixed-term, and temporary arrangements. These indicators reflect the extent to which a job provides not only financial security but also stability, opportunities for advancement, and a sense of job satisfaction as well as fulfilment for the worker. A high-quality employment opportunity offers sustainable income, long-term stability, and potential for career growth, while also ensuring fair and equitable treatment of employees.

Although the SHIW offers many variables that help grasp the quality dimension of employment, the financial stability of earnings appears to be the main employment outcome when it comes to young Italian workers. The success of earnings is important in the worrying context of in-work poverty, described by Berloffia et al. (2019) as a condition in which household disposable income is not enough to avoid poverty, even in a condition of medium- to long-term employment. This variable is insightful because it shows that, even if a person is employed, they might not be working enough to pass the poverty threshold (Berloffia et al., 2019). Furthermore, the concept of in-work poverty shifts the focus from unemployment to poverty, and looking at how different parts of the earnings distribution react to different backgrounds can elucidate policy initiatives. Therefore, I choose the quantile distribution of the log of net labour income as the main dependent variable for equations 5.1 and 5.2. I calculate the relationship between the background and the interaction variables and the log of labour income at the 0.20, 0.40, 0.60, 0.80, and 0.95 quantiles. To get an easier grasp of how the model works, the coefficient at the 0.20 quantile, also defined 20th percentile, indicates how changes in the independent variables impact the log of labour income for individuals at the lower end of the income distribution, while the coefficient at the 95th percentile reveals the relationship between the variables

for individuals at the upper end of the income distribution.

In the robustness checks of the empirical analysis, I also consider alternative employment outcomes available in the SHIW to explore whether the distribution of earnings is a valid measurement of employment quality in Italy. Using logistic and multinomial logistic regressions, I test the same relationships with three more employment quality indicators - employment duration, contract type, and part-time work. Employment duration captures the time dimension of employment quality - whether an individual has a stable job throughout the whole year or not. The contract type variable highlights under what legal circumstances an individual is hired and what benefits come from such employment. Lastly, part-time work is a more complicated indicator of employment quality, but the assumption is that an individual who holds a part-time occupation might not have enough means to get out of poverty.

From an analytical perspective, both employment duration and part-time work are binary outcomes - the former takes the value of 1 if the worker is employed throughout the whole year and 0 otherwise, while the latter takes the value of 1 if the individual has a part-time occupation and 0 otherwise. Therefore, I deploy a logistic regression model, as it is well-suited for estimating the probability of an event occurring (e.g., being employed throughout the whole year or having a part-time occupation) given the values of the independent variables. Since the contract type variable has three categories - permanent, fixed-term, and temporary contract -, I use a multinomial logistic regression, which is more suitable when the outcome variable has more than two categories.

5.2.2 Independent variables

Notwithstanding the long tradition in the economic literature to proxy an individual's background by parental education (Argentin and Triverti, 2010; Berloffia et al., 2011), one of the main contributions of this thesis is a more comprehensive definition of background. Firstly, an individual's background is affected by both economic and social aspects. Parental education may explain a big deal of the social capital inherited by children, and hence influence their education and employment choices and opportunities. Household wealth differentials, on the other hand, might explain the reason why people with the same ability, but who are presented with different financial opportunities, end up in different employment outcome categories. For example, financial constraints might limit a person from receiving a tertiary education, migrating, or opening a business. Following is a description of the process of construction of the independent variables of interest.

Information on parental education is available in the SHIW with two separate variables: the father's and the mother's educational attainment. Both variables of interest classify categories based on the person's attainment: none, primary school, middle school, high school, graduate, post-graduate, and unaware. In theory, it would be optimal to include both variables separately in my equations. However, I include a unique parental education index for different reasons. Firstly, the aim of this thesis is to consider the overall effect of parental education on employment

in Italy, taking the parents as a whole. I believe in the importance of providing a holistic view of how parental education, regardless of which parent it pertains to, impacts employment prospects. Secondly, many existing studies tend to use a single parental education measure rather than considering the two types of education separately. A unique measure of parental education aligns my results with the existing literature, allowing for easier interpretation and integration into the existing body of knowledge on the topic. Lastly, the father's and mother's educational attainments tend to be highly correlated, leading to multicollinearity issues when included as separate variables in the regression model. By creating a composite parental education index, it is possible to mitigate multicollinearity concerns.

In order to combine the two variables, I have followed the Human Development Index (HDI) technical note (Human Development Reports, 2010). Following is the equation for the calculation of each parent's index:

$$\text{Dimension index}_{it} = \left(\frac{\text{ActualValue}_{it} - \text{MinimumValue}}{\text{MaximumValue} - \text{MinimumValue}} \right) \quad (5.3)$$

Following equation 5.3, to calculate each parent's index, I divided the difference between the actual parent's education and the minimum education in each group by the difference between the maximum and the minimum education in each group. Consequently, I followed equation 5.4 to obtain the parental education index:

$$\text{Parental Education}_{it} = I_{\text{Father's Education}}^{\frac{1}{2}} * I_{\text{Mother's Education}}^{\frac{1}{2}} \quad (5.4)$$

Therefore, the parental education variable reports the square root of the product of the father's and the mother's education index. In other words, the index captures the average value of an individual's parental education. Both equations provide an individual-level index, characterized by the suffix $i = 1, 2, \dots, n$ at time t .

Regarding the wealth class variable, the SHIW provides information on household-level wealth, income, and consumption. The decision to use wealth information comes from the fact that poor people can resort to their financial assets in periods of crisis. Therefore, wealth data shows to a deeper extent the financial ability of Italian households. From the survey year 1991, the SHIW also includes a *Wealth Class* variable that reports the wealth distribution of Italian households across deciles.

In my model, I also include the interaction of the parental education index and wealth class with two demographic variables: gender and area of residence. The literature thoroughly explains the relationship between an individual's social background and employment opportunities. Gender gap studies focus on differentials between men and women in accessing the labour market and achieving higher wages, particularly in Italy (McGinn and Oh, 2017). However, it does not explain how different categories of gender and geographic areas interact with the social and economic background in shaping labour market opportunities. Hence the decision to include the interaction terms.

My model includes an interaction of gender - a binary variable that takes the value of 1 if female and 0 if male - with wealth class - grouped in deciles -, and an interaction of gender with the parental background index - *Wealth Class * Female* and *Parental Education * Female*. Given the fact that the Italian territory is divided into twenty regions and the SHIW provides a variable that records the region of residence for every individual, I constructed a geographic area variable that takes the value of 1 if the individual resides in a Southern region and 0 if the individual resides in a Northern region. Following the traditional division of the country, the North includes the North-Eastern and North-Western regions, as well as most of the central area - Tuscany, Lazio, Marche, and Umbria -, while the South includes the typical Southern regions - Abruzzo, Molise, Campania, Calabria, Apulia, and Basilicata - and the islands. I further created an interaction variable between the South dummy and the background variables separately, ultimately ending up with two geographic interaction variables - *Wealth Class * South* and *Parental Education * South*.

5.2.3 Control variables

Other than controlling for individual-level fixed effects, I also control for age group and education. Age is a crucial variable in my analysis because this thesis also aims to explore if young people are particularly disadvantaged compared to their adult counterparts in the labour market, following the findings by Berloffia et al. (2019) and Leonardi and Pica (2015). The SHIW includes both a continuous age variable and a group age variable. To show how the young group reacts to different backgrounds in relation to an employment outcome, it is relevant to consider the young age group (0 to 30) as a baseline in both the quantile and logistic regressions. This way, it is possible to see how age groups react across different quantiles of the income distribution, as well as how the probability of an individual belonging to a specific outcome category changes by moving from the young age group to an older age group.

The economic literature famously explored the positive relationship between educational attainment and different employment variables (Adda and Trigari, 2016; Berloffia et al., 2019). In particular, the theoretical framework by D'Agostino and Regoli (2012) identifies education as the mechanism through which parental decision to invest in education affects their children's employment opportunities. Therefore, it is important to control for educational attainment because it is very likely to influence the probability of an individual belonging to an outcome category. The SHIW divides the education variable into six different attainment levels: none, primary school, middle school, high school, graduate, and post-graduate.

5.2.4 Quantile estimates and predicted values

To ease the interpretation of the results of the quantile regression model, I deploy margin plots of the quantile estimates by category of age and education. For the remaining outcomes, including contract type, part-time work, and employment duration, predicted values are used to graphically explore the likelihood of each out-

come occurring given the values of the independent variables in the model. These predicted values are calculated by estimating the average effect of each independent variable on the outcome, holding other variables constant at their means. The aim is to help visualize how the prediction of each outcome varies across different levels of age and education.

6

Empirical Analysis

The empirical analysis presents the results following the estimation of equations 5.1 and 5.2. It delves into how an individual's background, measured by parental education and household wealth, is related to the log of labour income distribution as a key measure of economic well-being. I explore the findings on (i) the relationship between socioeconomic background and the log of labour income in quantiles, and (ii) how the interaction between an individual's background with gender and area of residence is related to the income distribution. I also include a graphical representation of the quantile estimates for a better interpretation of the results.

Table 6.1 shows the results of the quantile regression, with the log of labour income as the outcome variable. The first column presents the relationship between parental education and household wealth class and the log of labour income, while the second and third columns show the relationship between the interaction terms and the outcome variable. While all columns control for individual-level fixed effects and age groups, the third column also controls for educational attainment. The different panels of the table present the regressions at the following quantiles: 0.20, 0.40, 0.60, 0.80, and 0.95.

Column 1 of Table 6.1 shows the estimation of equation 5.1. It presents the relationship between an individual's background and the log of labour income in quantiles. As can be seen from the coefficients throughout the panels, the magnitude of the coefficient for the wealth class variable decreases as quantiles increase, while the significance increases as quantiles go up. This implies that while wealth may have a diminishing impact at higher income levels, it still plays a significant role in shaping income disparities across the income distribution. This result confirms Hypothesis 1, which predicts that as the household wealth class increases, an individual enjoys better employment conditions. On the other hand, parental education is only significant at the 0.60 and 0.80 quantiles, suggesting that the variable has a more pronounced effect on the log of labour income among individuals in the middle to upper percentiles of the income distribution. This implies that higher parental education levels are associated with a higher log labour income, particularly among individuals in these income brackets. The result confirms Hypothesis 2, which associates an improvement in employment stability with higher parental education.

Overall, the results in Column 1 are consistent with the theoretical framework

Table 6.1: Quantile regression. Outcome variable is Log of Labour Income

	(1)	(2)	(3)
	Labour Income	Labour Income	Labour Income
Panel A: 0.20 Quantile			
Wealth Class	0.018*		
	(1.88)		
Parental Education	0.045		
	(0.66)		
Wealth Class*Female		-0.012***	-0.014***
		(-5.42)	(-5.9)
Wealth Class*South		0.040***	0.042***
		(6.22)	(6.31)
Parental Education*Female		-0.009	-0.011
		(-0.49)	(-0.58)
Parental Education*South		0.028	0.027
		(0.56)	(0.54)
Panel B: 0.40 Quantile			
Wealth Class	0.016***		
	(2.62)		
Parental Education	0.047		
	(1.00)		
Wealth Class*Female		-0.012***	-0.014***
		(-7.37)	(-7.64)
Wealth Class*South		0.040***	0.041***
		(8.27)	(8.03)
Parental Education*Female		-0.012	-0.013
		(-0.84)	(-0.91)
Parental Education*South		0.042	0.041
		(1.14)	(1.05)
Panel C: 0.60 Quantile			
Wealth Class	0.015***		
	(6.64)		
Parental Education	0.051***		
	(3.02)		
Wealth Class*Female		-0.013***	-0.014***
		(-9.58)	(-8.28)
Wealth Class*South		0.038***	0.039***
		(10.23)	(8.4)
Parental Education*Female		-0.016	-0.018
		(-1.52)	(-1.31)
Parental Education*South		0.070**	0.069*
		(2.42)	(1.9)

	(1)	(2)	(3)
	Labour Income	Labour Income	Labour Income
Panel D: 0.80 Quantile			
Wealth Class	0.015*** (4.59)		
Parental Education	0.053** (2.23)		
Wealth Class*Female		-0.013*** (-8.02)	-0.014*** (-6.98)
Wealth Class*South		0.038*** (8.42)	0.039*** (6.99)
Parental Education*Female		-0.018 (-1.40)	-0.019 (-1.21)
Parental Education*South		0.080** (2.31)	0.079* (1.84)
Panel E: 0.95 Quantile			
Wealth Class	0.014** (2.41)		
Parental Education	0.055 (1.28)		
Wealth Class*Female		-0.013*** (-5.94)	-0.014*** (-5.32)
Wealth Class*South		0.037*** (6.07)	0.038*** (5.22)
Parental Education*Female		-0.020 (-1.17)	-0.021 (-1.03)
Parental Education*South		0.094** (2.00)	0.093* (1.66)
Age Group	Yes	Yes	Yes
Education	No	No	Yes
Fixed effects	Yes	Yes	Yes
<i>N</i>	72,854	72,854	72,854

Notes: *t* statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panels A through E report the quantile estimates of the relationship between socioeconomic background and the income distribution respectively at the 0.20, 0.40, 0.60, 0.80, and 0.95 quantiles.

Source: Bank of Italy (2023). Survey on Household Income and Wealth (SHIW).

by D'Agostino and Regoli (2012), which suggests that social origin, defined by the socioeconomic status of the parents, determines the household choices of investment in education, and hence occupational stability. The findings also agree with the empirical literature by Argentin and Triverti (2010) and Berggren (2013), showing that parental education influences children's success by affecting their interests, motivation, and choices. The contribution of this thesis with respect to the relationship between an individual's background and employment stability is twofold: for the first time, employment stability is measured by financial stability (log of labour income); socioeconomic status comprehends both parental education and household wealth class. Therefore, it shows that parental education and wealth class influence the employment outcome, although in different parts of the income distribution, and probably through different mechanisms. Further research has the objective of identifying such mechanisms. Lastly, the non-significant coefficient of parental education at the 0.20, 0.40, and 0.95 quantiles suggests that the impact of this variable on the income distribution may not be uniform across the quantiles. This underscores the importance of considering the interaction between parental education and other factors such as gender and geography when analysing income disparities.

Column 1 also controls for age group and, as expected, as the quantiles increase, the coefficients for all age categories other than the baseline category (0-30 age group) generally increase in magnitude. This suggests that older age groups tend to have higher log labour income across different quantiles of the income distribution. For example, in the 0.20 quantile regression, the coefficient for the 31-40 years age category is 0.2552, indicating that individuals in this age group have a higher log labour income compared to the reference category (0-30 years) in the 20th percentile of the income distribution. This finding has two implications. The first is that as individuals grow older, they tend to earn higher incomes, which could be attributed to factors such as career progression, higher wages, and increased work experience. However, it also implies that young people in Italy start off at a relatively lower level of income with respect to any other age group, leaving young individuals in a vulnerable position. This finding confirms Hypothesis 5, which predicts that young people are more likely than older workers to have a disadvantage in the labour market. While this result is consistent with the agreement in the literature that the young population in Italy is overrepresented among the unemployed (Adda and Trigari, 2015), it also adds more evidence in favour of the in-work poverty issue: even when young people have a job, the remuneration is often not enough to improve their financial situation.

Columns 2 and 3 specifically delve deeper into the interaction of an individual's background with the demographic variables - gender and residence. While both columns include age group and individual-level fixed effects, the third specification also controls for educational attainment. To give an example of the interpretation of the coefficients, the -0.012 coefficient for the *Wealth Class * Female* variable at the 0.20 quantile, statistically significant at the 1 percent level, means that at the 20th percentile of the log of labour income, a one-unit increase in wealth class is associated with a decrease in the log of labour income for females compared to males by 0.012 units. This result suggests that wealth has a slightly negative impact on labour income for females relative to males in the lower part of the income dis-

tribution. Across both specifications, while the interaction of gender with parental education is non-significant, the interaction of gender with wealth class yields a significant and negative coefficient, suggesting that wealth class has a higher impact on males compared to females when it comes to labour income distribution. This implies that even with similar levels of wealth, females may earn less than males, indicating potential gender-based disparities in labour market outcomes. This result confirms Hypothesis 3, which predicts that female workers from a lower socioeconomic status are less successful than their male counterparts in the labour market. This result is consistent with the finding by Berloffia et al. (2019) that the unemployment rate in Italy is unbalanced against women. It also sheds more light on the untested prediction by McGinn and Oh (2017) that social background and gender ideologies influence women's employment opportunities.

Meanwhile, at the 20th percentile of the log of labour income, a one-unit increase in wealth class is associated with an increase in the log of labour income for individuals residing in the South compared to those in the North by 0.040 units. Therefore, wealth positively influences labour income more significantly for Southern residents than for those in the North at this income level. The positive coefficients for the interaction between wealth class and geographic area across all quantiles and specifications suggest that individuals in the South experience a stronger impact of household wealth on labour income compared to those in the North. When combined with the negative wealth-gender interaction coefficients, this indicates that female workers in the South may face a compounded disadvantage, where their labour income is not only lower due to gender but also less responsive to wealth accumulation compared to males in the same region. The geographic interaction variable with parental education also becomes significant at the middle and top of the distribution: the positive and increasing magnitude implies that parental education affects individuals' employment outcomes differently across geographic areas. The progressively higher magnitude and significance of the β_4 coefficients indicate that the impact of parental education on labour income becomes progressively stronger in the higher percentiles of the income distribution, particularly for individuals residing in the South compared to those in the North. This could imply that the South may offer greater economic rewards for individuals with higher levels of parental education compared to the North. Alternatively, the results may reflect differences in socioeconomic mobility between regions, with individuals with highly educated parents in the South having better prospects for upward mobility and achieving higher incomes compared to their counterparts in the North.

These findings agree with the disproportionately higher unemployment in the South with respect to the North (Leonardi and Pica, 2015), as well as with Hypothesis 4, which predicts that Southern workers from a lower socioeconomic background are more disadvantaged in the labour market compared to their Northern counterparts. While research performs quite well in describing the disadvantage faced by female workers in the country, the literature on regional disparity is often limited to summary statistics and graphical interpretations of unemployment levels and rates. By studying the interaction between geographic residence and socioeconomic background, this thesis contributes to our understanding of the disproportionate labour market disadvantage that Southern Italians face, bringing evidence of a deeper sta-

tistical pattern.

Lastly, I would like to bring attention to the importance of age and education in determining the level of labour income at different quantiles of the income distribution. Both the second and the third specifications confirm the age group coefficients of the first specification, showing that across all quantiles the young group of people, on average, achieves lower wages and income than any older age group. Figure 6.1 also shows the margins plot of the quantile estimates by the different categories of age groups in ascending order. It is clearly visible that the log of labour income on average increases at every age group and the youngest remain the most disadvantaged, bringing new evidence in favour of Hypothesis 5.

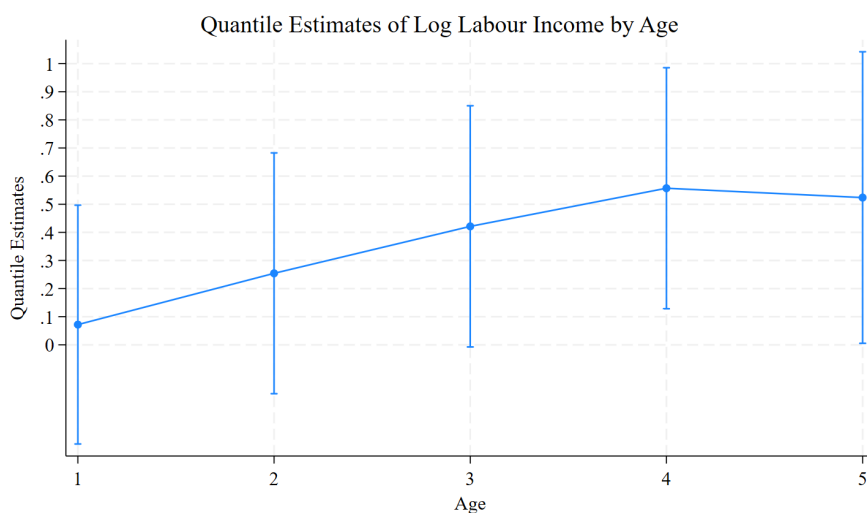


Figure 6.1: Margins plot of quantile estimates by Age Group. The y-axis reports the quantile estimates. The x-axis reports the different age groups in order: 0-30; 31-40; 41-50; 51-65; 65+.

A similar graphical pattern holds for the quantile estimates of the log of labour income by educational attainment in Figure 6.2. As the categories of education diverge from the "no education" category, the expected labour income increases. Looking at the third specification of Table 6.1, in the 0.20 quantile, the coefficients for education are generally not statistically significant, except for the graduate category, which has a positive and significant coefficient in some quantiles. As the quantiles increase, the coefficients for education become more significant and generally increase in magnitude, indicating a stronger association between higher education levels and higher log labour income. While the table proves the importance of education in predicting a quantile's average earnings, there appears to be no direct benefit from increasing education by one unit. The advantage of education is inherited only after a person graduates from high school, and the significance of the variable only appears in the upper part of the distribution. This result is consistent with the finding that unskilled workers are overrepresented among the unemployed in the country (Adda and Trigari, 2016). It also confirms the prediction by Berloff et al. (2019) that education plays a crucial role in delivering job security given the graduate advantage, especially in the Italian context where, as Iannelly and Smyth

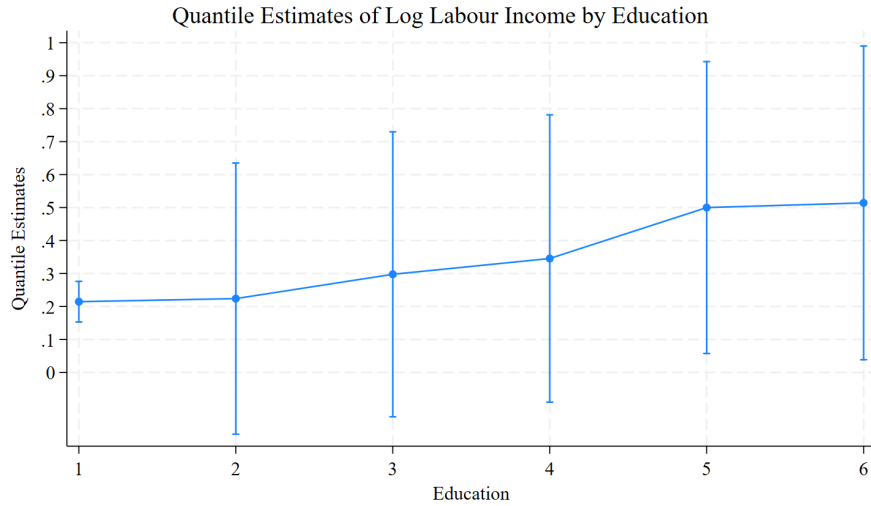


Figure 6.2: Margins plot of quantile estimates by Education. The y-axis reports the quantile estimates. The x-axis reports the different education categories in order: none; primary school; middle school; high school; graduate; post-graduate.

(2008) find, almost all the distance in employment opportunities can be explained by differences in education. However, this result is not in line with Leonardi and Pica (2015), who state that a university degree does not attribute an advantage in the labour market.

7

Robustness Checks

As part of the robustness checks, I present the results of the logistic and multinomial logistic regressions on the relationship between an individual's background, measured by household wealth class and parental education, the interaction terms, and three employment outcomes that are indicative of employment quality - employment duration, contract type, and part-time work. The reason behind this process is to show that the evidence brought by the previous analysis is not limited to the log of labour income. The precariousness of the labour market, mostly experienced by young individuals, female, and Southern workers, can be measured through different dimensions of employment: they are more likely to hold weaker contract types, receive lower net labour income, work for only part of the year compared to working through the whole year and hold a part-time vis-à-vis a full-time job. Had the predicted probabilities of the following models confirmed the hypotheses in Section 3.3, the log of labour income would be a good predictor of the stability of an individual's employment condition in Italy.

7.1 Employment Duration

The first alternative indicator of employment stability in Italy available in the SHIW since 1977 is employment duration. The relevance of the employment duration variable stems from the importance of the time dimension in the definition of employment quality. While labour earnings are fundamental to consider whether the job gives enough means to the worker to sustain themselves, employment duration deals with the stability of an employment condition through time. In the absence of stable employment through time, a worker might find themselves in a precarious living condition.

The employment duration variable takes the value of 1 if an individual was employed throughout the whole year at the time of the interview, and 0 otherwise. Given the nature of the binary variable, the best available method to explore its relationship with an individual's background is the logistic regression. To conduct the analysis, I use a fixed-effects logit model, which has the advantage of implicitly controlling for unobserved heterogeneity due to hard-to-measure characteristics and reduces the problems of self-selection and omitted-variable bias. The fixed effects logit calculates the odds ratio effects of an independent variable. All else equal, with the increase of, e.g., parental education by 1 unit, the odds of working through

the entire year ($EmploymentDuration = 1$) against working only part of the year increases by the factor $exp(\beta)$. Following is the equation that I estimate:

$$\begin{aligned} Employment\ Duration_{it} = & \alpha + \beta_0 Wealth\ Class_{it} \\ & + \beta_1 Parental\ Education_{it} + \beta_2 Age\ Group_{it} + \epsilon \end{aligned} \quad (7.1)$$

where α controls for individual fixed effects, i stands for individual $i = 1, 2, \dots, n$ and t is a suffix for the year variable. Equation 7.1 predicts the probability of an individual, with a specific background, captured by the variables $WealthClass$ and $ParentalEducation$, to work through the whole year or only part of it, through the dependent variable $EmploymentDuration$. β_0 predicts the change in the odds of working the whole year compared to working only part of the year for a one-unit increase in wealth class, holding all other variables constant, while β_1 predicts the change in the odds of working the whole year compared to working only part of the year for a one-unit increase in parental education.

The second equation that I estimate in the empirical analysis is focused on the interaction between social and economic background and demographic characteristics - i.e., gender and area of residence - and its effect on the probability of working through the whole year:

$$\begin{aligned} Employment\ Duration_{it} = & \alpha + \beta_0 Wealth\ Class * Female_{it} + \beta_1 Wealth\ Class * South_{it} \\ & + \beta_2 Parental\ Education * Female_{it} + \beta_3 Parental\ Education * South_{it} + \beta_4 X_{it} + \epsilon \end{aligned} \quad (7.2)$$

Equation 7.2 adds the interaction terms to explore how demographic characteristics interact with socioeconomic background variables to influence employment duration. I also include all additional covariates X , such as age group and educational attainment, that may influence employment duration but are not directly related to the interaction between socioeconomic background and demographic characteristics¹.

Table 7.1 shows the relationship between background, interaction terms, and employment duration. The coefficients report the log-likelihood of an individual working for only part of the year compared to working through the whole year. While wealth class appears to be non-significant (column 1), higher levels of parental education are significantly associated with a higher likelihood of being employed throughout the whole year compared to being employed only for part of the year, confirming Hypothesis 2. The interaction coefficients also offer interesting insights into the relationship between background and duration. Firstly, female workers seem to be disadvantaged because wealth class is negatively associated with the probability of working through the entire year for women with respect to men, confirming Hypothesis 3. On the other hand, higher levels of parental education are associated with a higher probability of working throughout the whole year for female workers with respect to male workers. Lastly, workers residing in the South are significantly more likely to work through the entire year as their wealth class increases, indicating that wealth class plays a bigger role in the South compared to the North. Looking

¹To ensure the reliability of the estimates, I have checked that the equations show linearity, homoscedasticity, and the absence of multicollinearity. Figures A.7, A.8, and Table A.1 respectively test for the linearity of predictors, homoscedasticity, and multicollinearity.

Table 7.1: Logistic Regression. Outcome variable is Employment Duration

	(1)	(2)	(3)
	Duration	Duration	Duration
Wealth Class	0.0326 (1.69)		
Parental Education	0.628*** (4.47)		
Wealth Class*Female		-0.0305** (-2.63)	-0.0327** (-2.79)
Wealth Class*South		0.128*** (3.39)	0.129*** (3.41)
Parental Education*Female		0.319** (2.99)	0.318** (2.96)
Parental Education*South		-0.00600 (-0.02)	-0.0139 (-0.05)
Age Group	Yes	Yes	Yes
Education	No	No	Yes
Fixed effects	Yes	Yes	Yes
<i>N</i>	8164	8164	8164

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Bank of Italy (2023). Survey on Household Income and Wealth (SHIW).

at how each age group compares to the baseline category of young individuals (0-30 years), all age groups have a lower likelihood of being employed for only part of the year. This finding confirms Hypothesis 5 and is in line with the literature claiming that young individuals suffer from higher job precariousness in Italy. This result is also evident in the graphical representation of the predicted probabilities by age groups in Figure A.9. The margin plot clearly shows a higher probability of the young group belonging to the part-of-year category and a lower probability of the same group belonging to the whole-year category compared to any other age group.

Table 7.1 also shows that education level does not seem to be significantly associated with a lower or a higher likelihood of being employed for the whole year compared to the baseline. However, Figure A.10 shows that unskilled workers are less likely to belong to the whole-year category than any other education group.

7.2 Contract Type

The stability of employment can also be measured through the contract type variable, available in the SHIW since the 2002 wave, allowing me to consider a nine years panel in the analysis. The contract type variable deals with access to stable employment contracts, and it became a relevant measure of employment stability after the implementation of the three policy interventions of the previous decades - the 1997 “Treu-Package”, the 2003 “Biagi Law”, and the 2016 “Jobs Act”. In recent decades, many authors have underscored how youth unemployment decreased in Italy over time, while temporary contracts are on the rise. Given that temporary and more

flexible contracts are associated with precarious employment conditions, which increases employment insecurity (Barbieri, 2009; Naswall and De Witte, 2003), it is important to consider the nature of employment as another outcome variable in the study.

Drawing on established literature (Berloffia et al., 2011; Argentin and Triventi, 2010), and given the nature of the categorical variable, I rely on the multinomial logit model. This model estimates the probabilities of multiple possible outcomes in a categorical choice situation. The contract type variable has three categories: permanent, fixed-term, and temporary. I employ a multinomial logit with individual-specific fixed effects to account for time-invariant unobserved heterogeneity among individuals. This method predicts the probability of an individual belonging to a specific contract type category - fixed-term or temporary category, with the permanent category as the baseline. Again, I explore first the relationship between an individual's background and the probability of an individual belonging to a specific contract type category compared to the baseline. The multinomial logistic regression equation that I estimate is formulated as follows:

$$\begin{aligned} \text{Contract Type}_{it} = \text{logit}(P) = \ln \left(\frac{P}{1 - P} \right) = & \alpha + \beta_0 \text{Wealth Class}_{it} \\ & + \beta_1 \text{Parental Education}_{it} + \beta_2 \text{Age Group}_{it} + \epsilon \end{aligned} \quad (7.3)$$

In equation 7.3, P represents the probability that an individual falls into a specific contract category, while α denotes individual-level fixed effects. The β_0 , β_1 , and β_2 are coefficients associated with wealth class, parental education, and age group, respectively. If the β_0 is positive, it suggests that individuals from higher wealth classes are more likely to belong to the specific contract type category compared to individuals from lower wealth classes, and vice versa for a negative coefficient. Likewise, a positive parental education coefficient indicates that individuals with higher parental education levels are more likely to belong to the specific contract category compared to individuals with lower parental education levels. Lastly, a positive age coefficient for a specific age group implies that individuals within that age group are more likely to belong to the specified employment outcome category compared to the reference age group (0-30 years).

The second model specification incorporates the interaction terms. This equation lets me explore how an individual's background interacts with gender and geographic area to influence the probability of belonging to a determined contract type. The model is written as follows:

$$\begin{aligned} \text{Contract Type}_{it} = \alpha + \beta_0 \text{Wealth Class} * \text{Female}_{it} + \beta_1 \text{Wealth Class} * \text{South}_{it} \\ + \beta_2 \text{Parental Education} * \text{Female}_{it} + \beta_3 \text{Parental Education} * \text{South}_{it} + \beta_4 \text{X}_{it} + \epsilon \end{aligned} \quad (7.4)$$

For the interaction terms, positive coefficients indicate that the interaction between the background variable and the specified demographic factor increases the likelihood of belonging to the contract category compared to the permanent type. More precisely, each interaction variable combines the effect of a demographic factor with wealth class and with the parental education index. For instance, a significant coefficient for the *WealthClass * Female* interaction suggests that the relationship

between wealth class and the likelihood of belonging to a contract type varies depending on gender. If the coefficient is positive, it indicates that the association between wealth class and a specific contract type is stronger for females compared to males ².

Table 7.2 shows the results of the multinomial logistic regression models with the contract-type variable as employment outcome and permanent contract as the baseline category. The coefficients need to be interpreted in terms of the likelihood of belonging to one of the other categories compared to the baseline. Panel A reports the results for the fixed-term contract category, and Panel B reports the results for the temporary contract category. While Panel B does not report any insightful results, Panel A presents an optimal case study. Column 1 of Panel A shows that wealth class appears to be significantly associated with a lower probability of being employed with a fixed-term contract compared to a permanent one, confirming Hypothesis 1. In other words, belonging to a higher wealth class in the wealth distribution facilitates the probability of accessing more secure employment contracts. However, the relationship between parental education and belonging to a fixed-term contract is not significant, and this is true for all indicators of an individual's background when it comes to temporary contracts (Panel B, column 1).

Delving deeper into the analysis, and looking at the interaction variables coefficients, columns 2 and 3 of Panel A show that the effect of wealth class varies across gender and geographic areas. Specifically, female workers are more likely to belong to the fixed-term contract category than their male counterparts, confirming Hypothesis 3. On another note, workers from the South are less likely to belong to the fixed-term contract category than their Northern counterparts. These results show evidence that female workers are disadvantaged in the labour market when it comes to accessing more secure employment contracts. On the other hand, it remains less clear how workers from the South are less likely to belong to a fixed-term contract. One possible explanation could be that the flexibilization reforms in the South are still on the way to being fully implemented, meaning that the traditional contract type is still the permanent one.

The lack of significance of the interaction coefficients in the third category - temporary contracts - might imply that there are other factors, such as age and education, that influence the probability of belonging to this category of contracts compared to a permanent one. In fact, while the coefficients of any interaction term are not significant, the 31-40 and 41-50 age groups are both less likely to get a temporary contract than the baseline young people's category, confirming Hypothesis 5. This is evidence that young people in Italy suffer from precarious labour conditions to a larger extent than older age categories. Furthermore, the strong and negative coefficients across all education levels support the interpretation that any education level is less likely to be employed under a temporary contract compared to workers with no education. This is also evidence that unskilled workers are more vulnerable to the lack of security in the job market.

²To derive reliable and unbiased estimates from the multinomial logit model, I tested three key assumptions: the linearity of predictors (Figure A.11), homoscedasticity (Figure A.12), and the absence of multicollinearity (Table A.1).

Table 7.2: Multinomial logistic regression. Outcome variable: Contract Type. Baseline: Permanent Contract

	(1)	(2)	(3)
	Contract	Contract	Contract
Panel A: Fixed-Term Contract			
Wealth Class	-0.0553*		
	(-2.40)		
Parental Education	-0.106		
	(-0.77)		
Wealth Class*Female		0.0400**	0.0373*
		(2.77)	(2.55)
Wealth Class*South		-0.131**	-0.133***
		(-3.28)	(-3.33)
Parental Education*Female		0.0313	0.0166
		(0.27)	(0.15)
Parental Education*South		-0.0260	-0.00826
		(-0.11)	(-0.03)
Panel B: Temporary Contract			
Wealth	-0.0678		
	(-1.23)		
Parental Education	0.0136		
	(0.04)		
Wealth Class*Female		0.0400	0.0410
		(1.07)	(1.05)
Wealth Class*South		-0.156	-0.172
		(-1.67)	(-1.85)
Parental Education*Female		0.104	0.0952
		(0.38)	(0.35)
Parental Education*South		-0.0281	-0.0241
		(-0.05)	(-0.04)
Age Group	Yes	Yes	Yes
Education	No	No	Yes
Fixed effects	Yes	Yes	Yes
<i>N</i>	6685	6685	6685

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Baseline category: Permanent Contract

Source: Bank of Italy (2023). Survey on Household Income and Wealth (SHIW).

Figure A.13 shows the adjusted predicted probability of an individual belonging to a specific contract type category by age group. The top-left panel shows that the predicted probability of belonging to the permanent contract category becomes higher as one moves from the young age category up to the 51-65 age group. Younger people are also more likely to be employed under a fixed-term contract than any other age group. On the other hand, Figure A.14 shows the adjusted predicted probability of an individual belonging to a specific contract type category by education level. The graphs confirm the results of the multinomial regression model with interaction terms: unskilled workers are less likely to get a permanent contract than any other category in the spectrum of skills, they are slightly more likely to get a fixed-term one, and even more so a temporary contract.

7.3 Part-Time Work

The part-time status of an employment position can also shed light on the precariousness of labour. The underlying assumption here is that a person who holds a part-time position might not have enough means to sustain themselves, and hence the part-time status can be considered a precarious job condition. The part-time work variable, available in the SHIW since 1986, is a binary variable that takes the value of 1 if the individual holds a part-time occupation, and 0 otherwise. Given the nature of the binary variable, I adopt the same model I used for the employment duration variable, explained in Section 7.1: a fixed-effects logit model, where the dependent variable is the part-time variable, and the explanatory variables of interest are (i) wealth class and parental education and (ii) the interaction terms. The first equation goes as follows:

$$\begin{aligned} \text{Part-Time Work}_{it} = & \alpha + \beta_0 \text{Wealth Class}_{it} \\ & + \beta_1 \text{Parental Education}_{it} + \beta_2 \text{Age Group}_{it} + \epsilon \end{aligned} \quad (7.5)$$

where α controls for individual fixed effects, i stands for individual $i = 1, 2, \dots, n$ and t is a suffix for the year variable. Equation 7.5 predicts the probability of an individual, given a specific background, captured by *WealthClass* and *ParentalEducation*, to hold a part-time position or not. β_0 predicts the change in the odds of holding a part-time position compared to not holding one for a one-unit increase in wealth class, holding all other variables constant, while β_1 predicts the change in the odds of working part-time compared to not working part-time for a one-unit increase in parental education.

The second equation, focused on the interaction of socioeconomic background with gender and area of residence, goes as follows:

$$\begin{aligned} \text{Part-Time Work}_{it} = & \alpha + \beta_0 \text{Wealth Class} * \text{Female}_{it} + \beta_1 \text{Wealth Class} * \text{South}_{it} \\ & + \beta_2 \text{Parental Education} * \text{Female}_{it} + \beta_3 \text{Parental Education} * \text{South}_{it} + \beta_4 X_{it} + \epsilon \end{aligned} \quad (7.6)$$

The interaction variables in Equation 7.6 capture how the relationship between wealth class and parental education with part-time work varies by gender and area

of residence. I also include all additional covariates X , such as age group and educational attainment, that may influence part-time work but are not directly related to the interaction between socioeconomic background and demographic characteristics.³

Table 7.3: Logistic Regression. Outcome variable is Part-Time Work

	(1)	(2)	(3)
	Part-Time	Part-Time	Part-Time
Wealth Class	-0.00186 (-0.09)		
Parental Education	-0.148 (-1.14)		
Wealth Class*Female		0.149*** (13.53)	0.147*** (13.27)
Wealth Class*South		-0.273*** (-6.84)	-0.272*** (-6.80)
Parental Education*Female		0.284** (3.03)	0.274** (2.93)
Parental Education*South		-0.570* (-2.29)	-0.560* (-2.25)
Age Group	Yes	Yes	Yes
Education	No	No	Yes
Fixed effects	Yes	Yes	Yes
N	7263	7263	7263

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: Bank of Italy (2023). Survey on Household Income and Wealth (SHIW).

Column 1 in Table 7.3 reports a non-significant relationship between an individual's socioeconomic background and part-time work. It appears that, within this model, individuals' decisions regarding part-time employment are not influenced by wealth or financial status, nor by their parents' educational attainment. However, it's important to consider that non-significance does not necessarily imply the absence of any relationship between socioeconomic status and part-time work. Socioeconomic background could interact with other demographic characteristics to influence the decision of part-time work.

Precisely, Columns 2 and 3 offer the results for equation 7.6, on the relationship between the interaction of status with gender and residence, and its effect on the likelihood of holding a part-time position. The results show that, for females, an increase in wealth class or parental education is associated with a significant increase in the log odds of holding a part-time job, holding other variables constant. This implies that socioeconomic background influences part-time work decisions more for females than for males, confirming Hypothesis 3. Also, the effect of wealth class and parental education on part-time employment is significantly affected by residence,

³To ensure the reliability of the estimates, I have checked that the equations show linearity (Figure A.15), homoscedasticity (Figure A.16), and the absence of multicollinearity (Table A.1).

with wealthier individuals in the South being less likely to hold a part-time position. This reflects a weaker impact of socioeconomic status on part-time work decisions in the South compared to other regions.

Looking at age, there is no significant difference in the likelihood of holding a part-time job compared to the reference group. However, individuals in the oldest age group (65+) are significantly more likely to work part-time, as they may choose part-time work for various reasons such as retirement transition, reduced work capacity, or lifestyle preferences.

8

Discussion and Final Remarks

The literature on wealth inequality and employment opportunities has identified some vulnerable groups that suffer from bad employment conditions. In Italy, young people, female workers, and individuals with residence in the South show consistently higher unemployment rates than the rest of the population. In the context of rising wealth inequality (Acciari et al., 2021; Dagnes et al., 2018; Brandolini et al., 2018) and bad economic conditions following the double-dip recession (Brandolini et al., 2018; Dagnes et al., 2018), it is possible to hypothesize that the vulnerable groups of society are more likely to inherit the effects of the recent macroeconomic transformations. Therefore, leaving behind traditional measures of employment status, this thesis aims to explore the employment quality these groups have faced in the last forty years.

Drawing on the agreements in the literature, I hypothesized five main arguments. Based on the linkage between poverty and worse employment opportunities (D'Agostino and Regoli, 2012) I expected that as we move along the household wealth class distribution, workers enjoy better employment conditions, all else being equal. The second hypothesis, supported by the work of D'Agostino and Regoli (2012), Argentin and Triverti (2010), and Berloffia et al. (2011), posits that individuals' labour market outcomes improve as their parental education increases, suggesting that higher levels of parental education positively influence children's employment prospects. The third hypothesis, based on the findings by McGinn and Oh (2017), which indicate that women's employment opportunities are influenced by background and gender ideologies, asserts that the interaction between gender and an individual's background results in female workers being significantly disadvantaged in the labour market compared to male workers. Based on contextual evidence of the significant regional divide in Italy (Leonardi and Pica, 2015; Dagnes et al., 2018), the fourth hypothesis suggests that workers residing in the South are more vulnerable to labour market disadvantages. Specifically, the interaction between geographic residence and an individual's background is expected to result in Southern workers being significantly disadvantaged in the labour market compared to their Northern counterparts. Lastly, the fifth hypothesis addresses age-related disparities in employment conditions. Drawing on empirical evidence from Berloffia et al. (2019) and Leonardi and Pica (2015), it is anticipated that different age groups will experience varying employment conditions, with young people being more likely to face disadvantages compared to older generations.

Using historical data on households' wealth and employment from the Survey on Household Income and Wealth (SHIW) by the Bank of Italy, I use a quantile regression model to explore the relationship between (i) an individual's socioeconomic background, measured by household wealth class and parental education, and their position in the labour income distribution; and between (ii) the interaction of socioeconomic status with demographic characteristics and the log of labour income. The panel spans from 1977 for some variables to 2020. This process brings two important contributions to our knowledge on the topic: firstly, I use a comprehensive measure of socioeconomic background, which encompasses the economic status through household wealth class, and the social aspect through parental education. Furthermore, while the literature extensively collects data and performs studies that identify the vulnerable groups of the population in the labour market, it does not explain how distinct demographic characteristics such as age, gender, and geographic residence, are related to an individual's socioeconomic background when it comes to employment opportunities.

I recognise two main limitations in my thesis. Firstly, although I conduct a significant panel data study that spans 40 years, I do not explicitly test for the temporal dimension or analyze how trends evolve. While I partially address this by including variables available at different survey years, a more thorough examination of temporal changes should be conducted in future research. Secondly, to measure the social dimension of an individual's background, I align with the common approach in the literature by constructing a parental education index, to ease the interpretation and the contextualisation of my results. However, based on the literature that identifies different channels through the father's and mother's education in influencing a child (Berloffia et al., 2011), future research should explore how different parents' education matters for children's opportunities.

The results from the empirical analysis confirm the hypotheses. Wealth class significantly predicts labour income at every quantile, while parental education only plays a role in the 0.80 quantile. Wealthier individuals, as well as Italians whose parents achieved a higher level of education, are advantaged in the financial labour market outcomes. This evidence supports that a higher socioeconomic status leads to better employment opportunities in Italy. Furthermore, it is interesting to pinpoint that the impact of wealth class on labour income diminishes as individuals move towards higher income percentiles. While wealthier individuals tend to earn more than those with lower wealth at lower income levels, the advantage diminishes as the income level increases. On the other hand, parental education shows a larger effect on earnings in the middle to upper percentiles of the distribution, implying that individuals with higher levels of parental education, on average, experience greater improvements in their financial outcomes, compared to those with lower parental education levels, especially in the higher quantiles. These findings confirm Hypothesis 1, which posits a positive relationship between wealth class and net labour income. The results also align with Hypothesis 2, which supports the idea that parental education positively impacts labour market outcomes. Although the literature already proves the effect of social background on employment opportunities in Italy, authors often rely on parental education as a proxy for the social

background of individuals, and this is one of the first empirical analyses also considering wealth to determine their economic status.

The literature also discusses the disadvantaged position of different categories in the labour market in the country. Some of these vulnerable groups are young people (Adda and Trigari, 2016; Leonardi and Pica (2015); Berloff et al., 2019), females (Berloff et al, 2019; McGinn and Oh, 2017; Berggren, 2013), individuals from the South (Leonardi and Pica, 2015), and unskilled workers (Adda and Trigari, 2016; Berloff et al., 2019; Argentin and Triverti, 2010). This thesis explores to what extent demographic characteristics interact with the socioeconomic status of individuals to determine their employment opportunities in Italy. Starting from the main employment outcome of the analysis, the log of labour income, I find that females with similar levels of wealth as males, still earn less than their male counterparts in the workplace, across all quantiles. This evidence in favour of gender-based disparities in labour market outcomes supports Hypothesis 3, which posits that female workers from lower socioeconomic statuses are disadvantaged in the labour market compared to male workers. This result also confirms the long-standing findings on gender-biased success in the labour market.

The results also indicate that wealth has a stronger impact on labour income for individuals residing in the South compared to those in the North, suggesting that the relationship between wealth and labour income distribution is more important in the South. The interaction effect shows that workers from the South are disadvantaged in the labour market, as they are more vulnerable depending on their wealth status, confirming Hypothesis 4. An even more interesting result is that if we combine this result with the positive gender-wealth interaction coefficient, women in the South face a compounded disadvantage, such that their level of earnings is not only lower than men's but also less responsive to wealth accumulation compared to males in the same area.

Regarding the argument that young people are more vulnerable than older age groups, the analysis reveals that older age groups tend to have higher labour income across different quantiles, while young individuals start off at a lower income level, consistent with Hypothesis 5. This suggests that young people in Italy face economic vulnerability compared to older age groups, which could be attributed to factors like career progression, work experience, but also the recent structural reforms of the labour market.

The robustness checks on alternative indicators of employment quality provide additional insights into the relationship between socioeconomic background and various dimensions of employment stability. These alternative measures serve as important complements to the analysis of log labour income, and show they all perform a good job at representing the labour quality conditions of different groups of workers in Italy. Higher parental education is associated with a higher likelihood of being employed throughout the whole year, suggesting that individuals with better-educated parents are more likely to experience stable employment conditions, all else equal. Individuals belonging to a higher wealth class in the wealth distribution have a higher probability of accessing more secure employment contracts. Female

workers are disadvantaged because they are more likely to belong to the fixed-term contract category than their male counterparts, and are more likely to hold part-time positions compared to male workers. Not only do these findings agree with the evidence in the literature, but they also expand it by considering different indicators of employment quality.

Bibliography

- [1] Acciari, P., Alvaredo, F., Morelli, S. (2021). The Concentration of Personal Wealth in Italy 1995–2016. <https://doi.org/10.31235/osf.io/2jznp>.
- [2] Adda, J., Trigari, A. (2016). Labor market inequalities across Italian demographic groups: a focus on the youth and the long-term unemployed. *Innocenzo Gasparini Institute for Economic Research*.
- [3] Agresti, A. (1996). An Introduction to Categorical Data Analysis. New York: John Wiley and Sons, Inc.
- [4] Argentin, G., Triventi, M. (2010). Social inequality in higher education and labour market in a period of institutional reforms: Italy, 1992-2007. *Springer Science+Business Media B.V.*, No. 61, pp. 309-323.
- [5] Banca d'Italia (2023). Survey on Italian Household Income and Wealth. Historical Database (all waves). Banca d'Italia.
- [6] Barbieri, P. (2009). Flexible Employment and Inequality in Europe. *European Sociological Review*, Vol. 25, No. 6, pp. 621–628.
- [7] Berggren, C. (2013). The influence of gender, social class and national background on education and work career? *Nordic Journal of Migration Research*, Vol 3, No. 3, pp. 135-144.
- [8] Berloffa, G., Matteazzi, E., Sandor, A., Villa, P. (2019). The quality of employment in the early labour market experience of young Europeans. *Cambridge Journal of Economics*, Vol. 43, No. 6, pp. 1549–1575.
- [9] Berloffa, G., Modena, F., Villa, P. (2011). Inequality of opportunity for young people in Italy: Understanding the role of circumstances. *Society for the Study of Economic Inequality (ECINEQ)*, Working Paper Series N. 241.
- [10] Bigoni, M., Bortolotti, S., Casari, M., Gambetta, D. (2019). At the Root of the North–South Cooperation Gap in Italy: Preferences or Beliefs? *The Economic Journal*, Vol. 129, No., 619, pp. 1139–1152. <https://doi.org/10.1111/ecoj.12608>.
- [11] Brandolini, A., Gambacorta, R., Rosolia, A. (2018). Inequality amid income stagnation: Italy over the last quarter of a century. Banca d'Italia, *Questioni di Economia e Finanza*, Occasional Papers No. 442.
- [12] Calvó-Armengol, A., Jackson, M. O. (2006). The Effects of Social Networks on Employment and Inequality. *The American Economic Review*, Vol. 94, No. 3, pp. 426-454

- [13] Cappellari, L., Dell’Aringa, C., Leonardi, M. (2012). Temporary Employment in Italy. *CESifo DICE Report. ifo Institut - Leibniz-Institut für Wirtschaftsforschung an der Universität München*, Vol. 10, No. 1, pp. 55-62.
- [14] Checchi, D., Peragine, V. (2009). Inequality of opportunity in Italy. *The Journal of Economic Inequality*. No.8, pp.429–450.
- [15] D’Agostino, A., Regoli, A. (2012). Life Conditions and Opportunities of Young Adults: Evidence from Italy in European Comparative Perspective. *Springer Science+Business Media B. V.*, Vol. 113, pp. 1205-1235.
- [16] Dagnes, J., Filandri, M., Storti, L. (2018). Social class and wealth inequality in Italy over 20 years, 1993–2014. *Journal of Modern Italian Studies*, Vol. 23, No. 2, pp. 176-198. <https://doi.org/10.1080/1354571X.2018.1427945>.
- [17] Dosi, G., Pereira, M. C., Roventini, A., Virgillito, M. E. (2018). The effect of labour market reforms upon employment and income inequalities: an agent-based model. *Socio-Economic Review*, Vol. 16, No., 4, pp. 687-720.
- [18] EIGE, (2023). Gender Equality Index 2023. Towards a green transition in transport and energy. *Publications Office of the European Union*.
- [19] Fanti, L., Pereira, M. C., Virgillito, M. E. (2023). The North-South divide: Sources of divergence, policies for convergence. *Journal of Policy Modeling*, Vol. 45, No. 2, pp. 405-429. <https://doi.org/10.1016/j.jpolmod.2022.10.007>.
- [20] Harrison, E., Rose, D. (2006). The European Socio-economic Classification. ESeC User Guide. Institute for Social and Economic Research.
- [21] Hosmer, D. and Lemeshow, S. (2000). Applied Logistic Regression (Second Edition). New York: John Wiley and Sons, Inc..
- [22] Iannelli, C., Smyth, E. (2008). Mapping gender and social background differences in education and youth transitions across Europe. *Journal of Youth Studies*, Vol. 11, No. 2, pp. 213-232.
- [23] Istat. (2024) Italian Labour Force Survey - Annual file.
- [24] Leonardi, M., Pica, G. (2015). Youth unemployment in Italy, in J. Dolado, No Country for Young People? Youth Labour Market Problems in Europe, London: CEPR Press, pp. 89-104.
- [25] Long, J. S. and Freese, J. (2006). Regression Models for Categorical and Limited Dependent Variables Using Stata, Second Edition. College Station, Texas: Stata Press.
- [26] Lucchini, M., Schizzerotto, A. (2010). Chapter 11: Unemployment risks in four EU countries. A validation study of the ESeC, in D. Rose and E. Harrison (1st ed), Social Class in Europe. An introduction to the European Socio-economic Classification, London: Routledge, pp. 235-244.
- [27] McGinn, K. L., Oh, E. (2017). Gender, social class, and women’s employment. *Current Opinion in Psychology*, Vol. 18, pp. 84-88.

- [28] Naswall, K., De Witte, H. (2003). Who Feels Insecure in Europe Predicting Job Insecurity from Background Variables. *Economic and Industrial Democracy*, Vol. 42, No. 2, pp. 189-215.
- [29] Odoardi, I. (2020). Youth unemployment: A serious problem for young Italians NEET and a comparison with the social exclusion condition. *Journal of Urban and Regional Analysis*.
- [30] Rios-Avila, F., Maroto, M. L. (2022). Moving Beyond Linear Regression: Implementing and Interpreting Quantile Regression Models With Fixed Effects. *Sociological Methods and Research*, Vol. 53, No. 2, pp. 639-682. <https://doi.org/10.1177/00491241211036165>
- [31] United Nations Development Programme (UNDP) (2010). Technical note 1. Calculating the Human Development Index. *Human Development Reports*.

Appendix A

Appendix

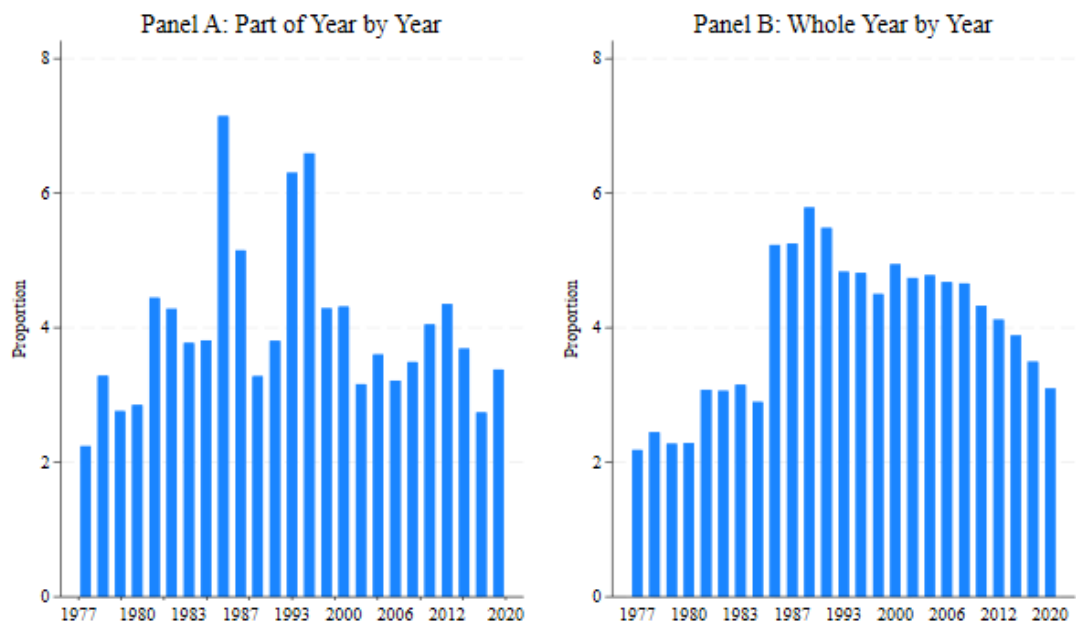


Figure A.1: Proportions of Employment Duration by Year.

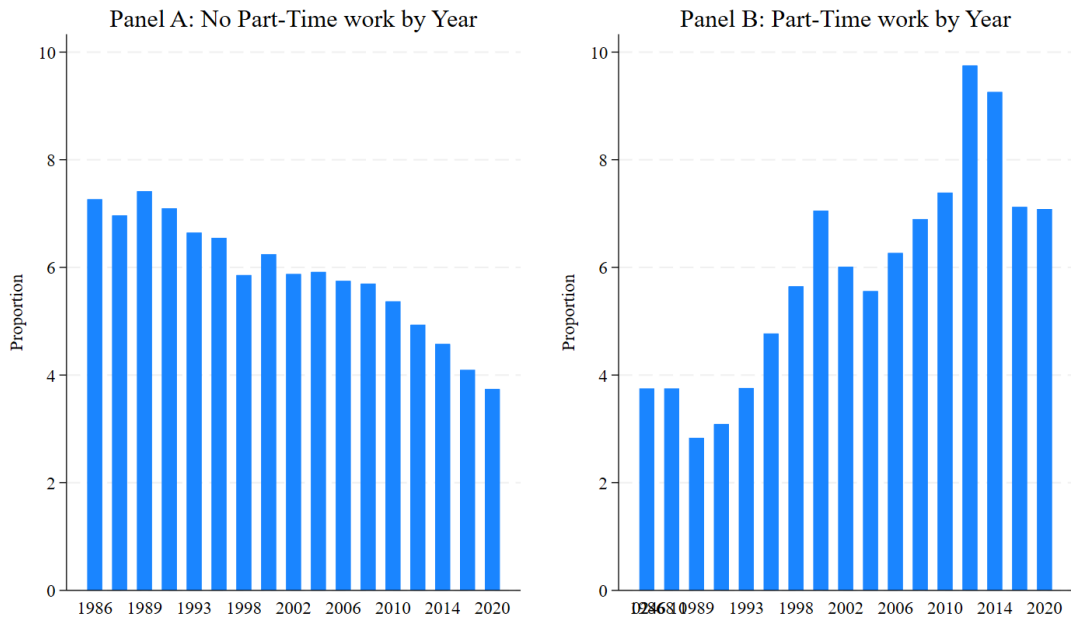


Figure A.2: Proportions of Part-Time work by Year.

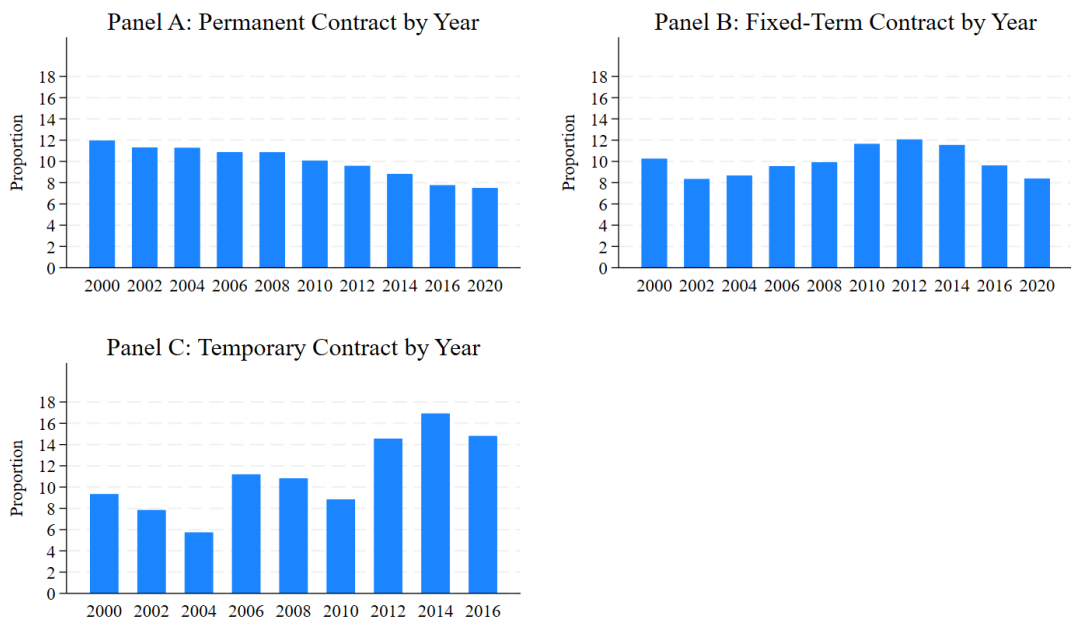


Figure A.3: Proportions of Contract Type by Year.



Figure A.4: Linearity of Predictors. Log of Labour Income against independent variables.

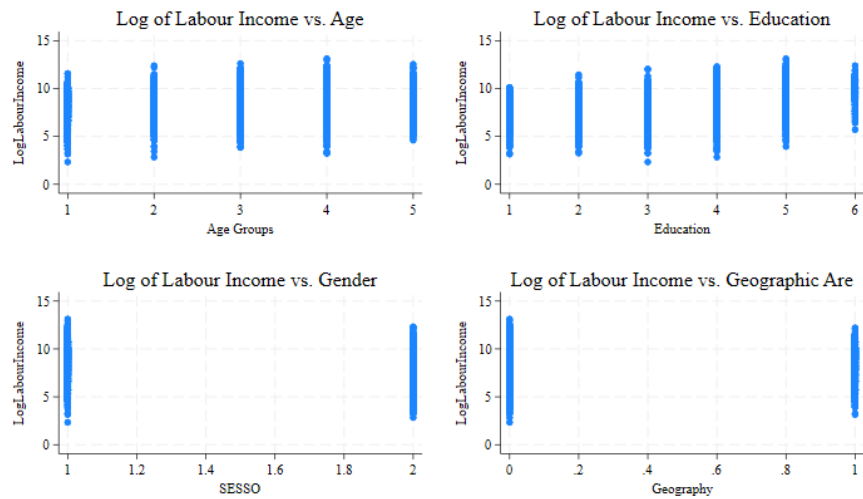


Figure A.5: Linearity of Predictors. Log of Labour Income against independent variables.

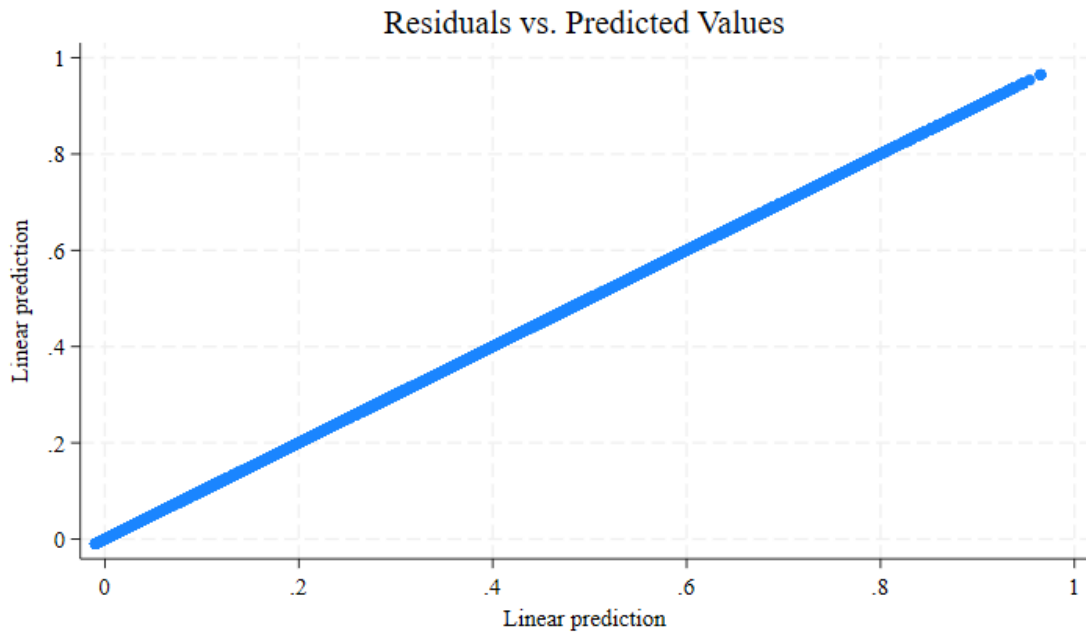


Figure A.6: Homoscedasticity. Residuals against predicted values. Dependent variable is Log of Labour Income.

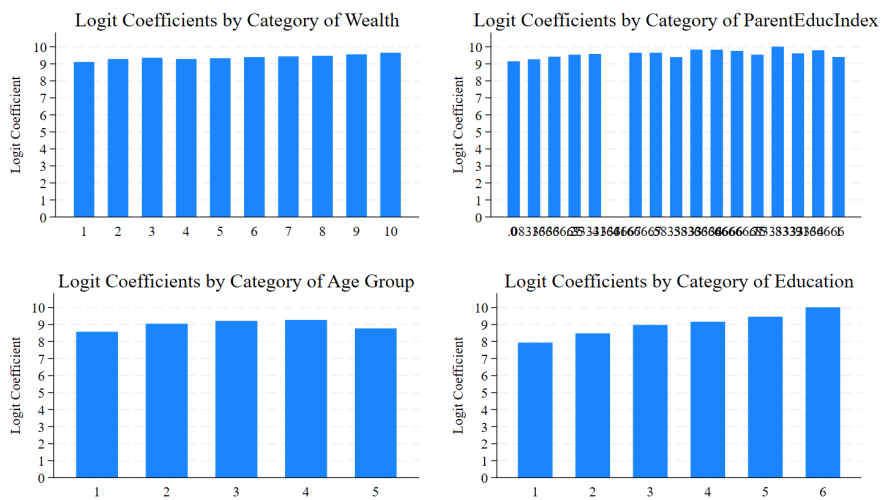


Figure A.7: Linearity of Predictors. Logit coefficients by Category of independent variables. Dependent variable is Employment Duration.

Table A.1: Correlation Matrix

	Wealth*Female	Wealth*South	ParentEduc*Female	ParentEduc*South	Age	Education
Wealth*Female	1.000					
Wealth*South	0.096	1.000				
ParentEduc*Female	0.173	-0.001	1.000			
ParentEduc*South	-0.071	0.486	0.472	1.000		
Age	0.0697	0.023	-0.010	0.011	1.000	
Education	0.209	0.045	0.134	0.010	-0.387	1.000

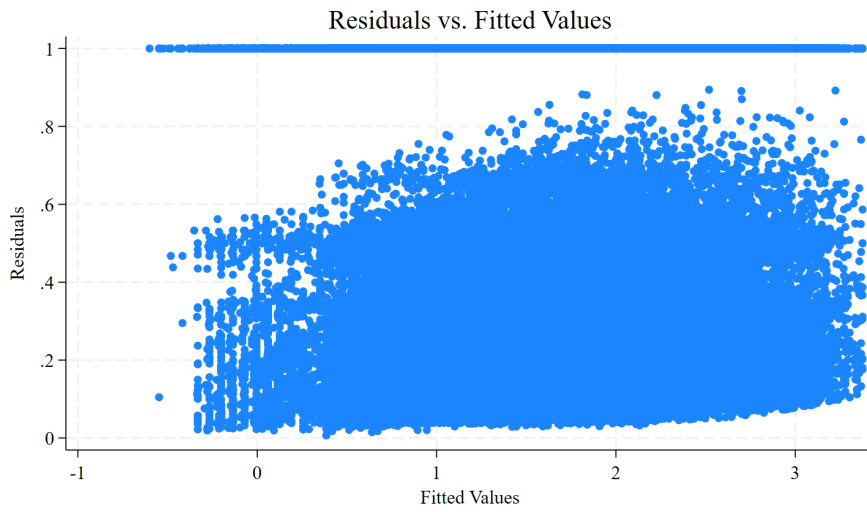


Figure A.8: Homoscedasticity. Residuals against predicted values. Dependent variable is Employment Duration.

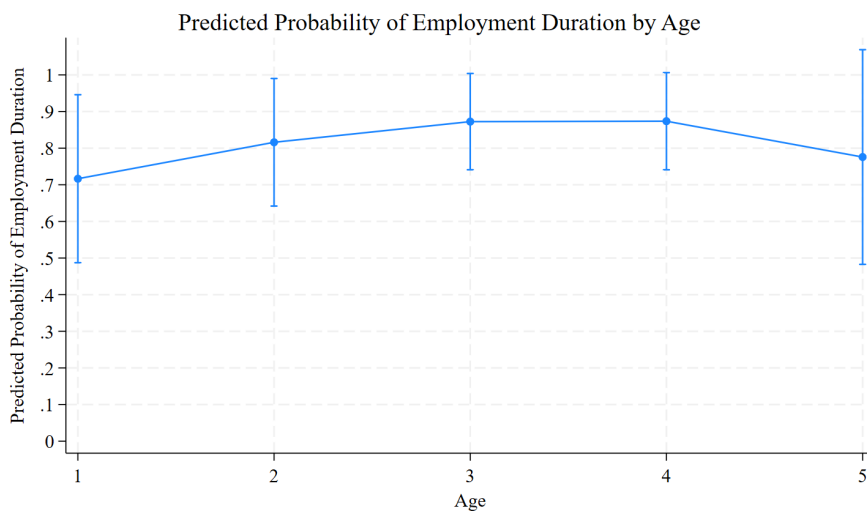


Figure A.9: Margins plot of predicted probabilities by Age Group for Employment Duration.

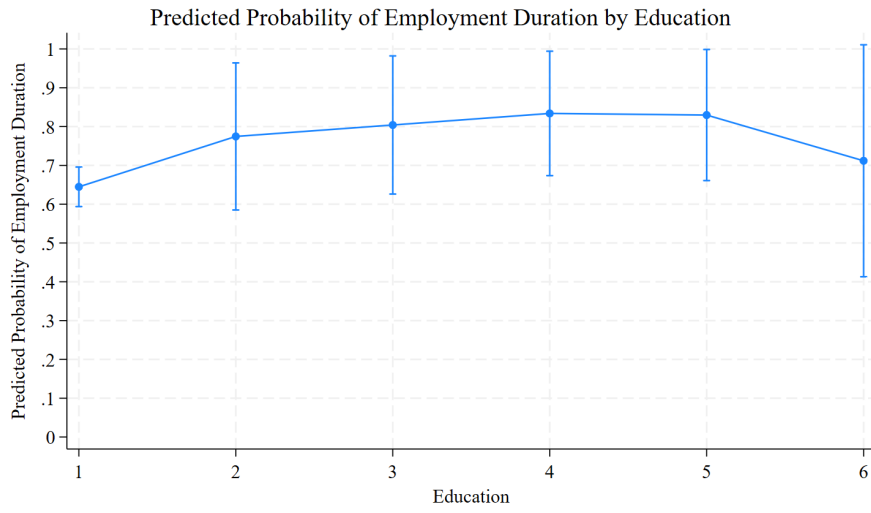


Figure A.10: Margins plot of predicted probabilities by Education for Employment Duration.

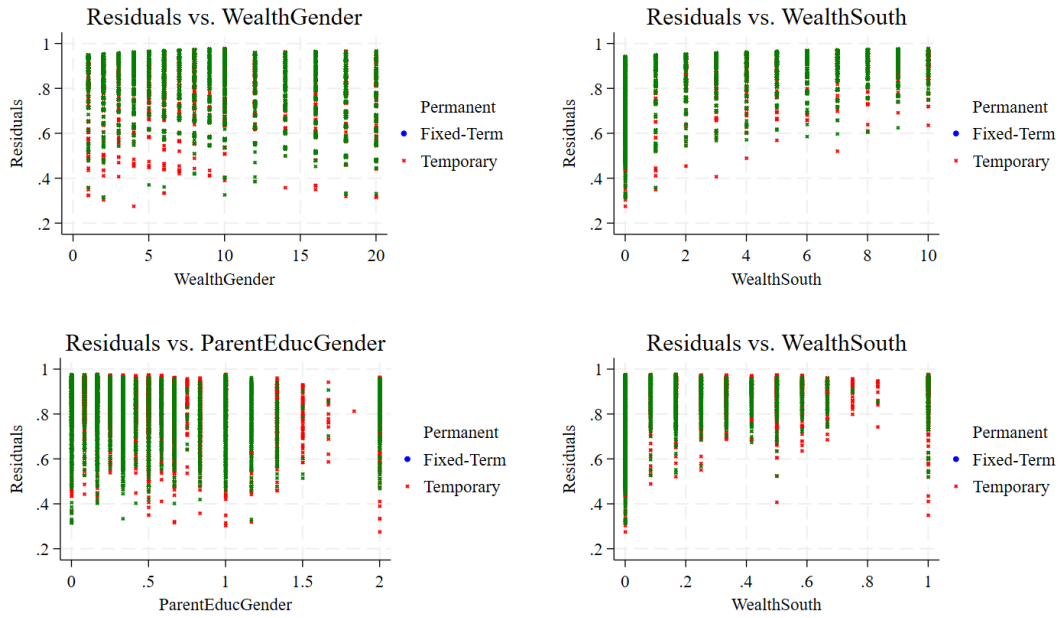


Figure A.11: Linearity of Predictors. Contract Type against independent variables.

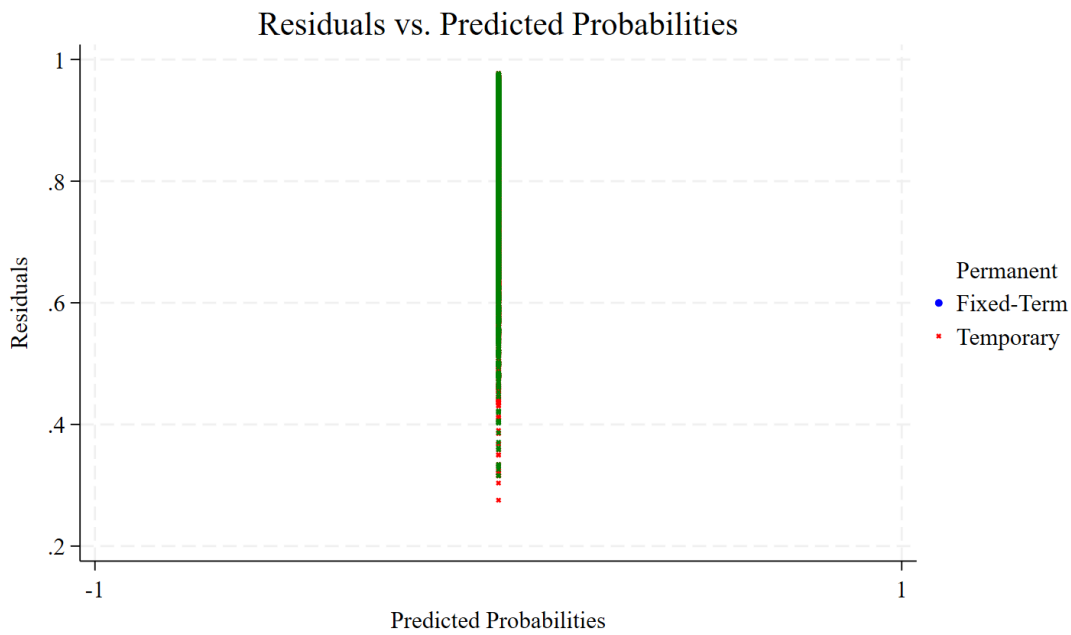


Figure A.12: Homoscedasticity. Residuals against predicted values. Dependent variable is Contract Type.

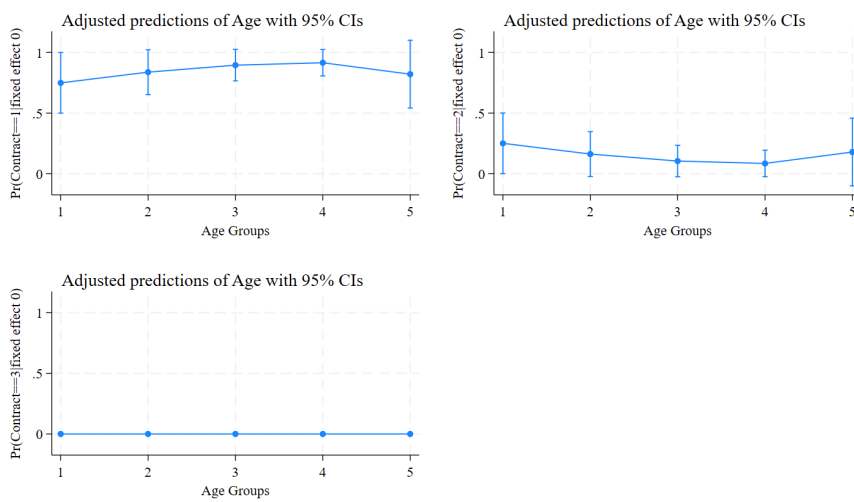


Figure A.13: Margins plot of predicted probabilities of Contract Type by Age Group.

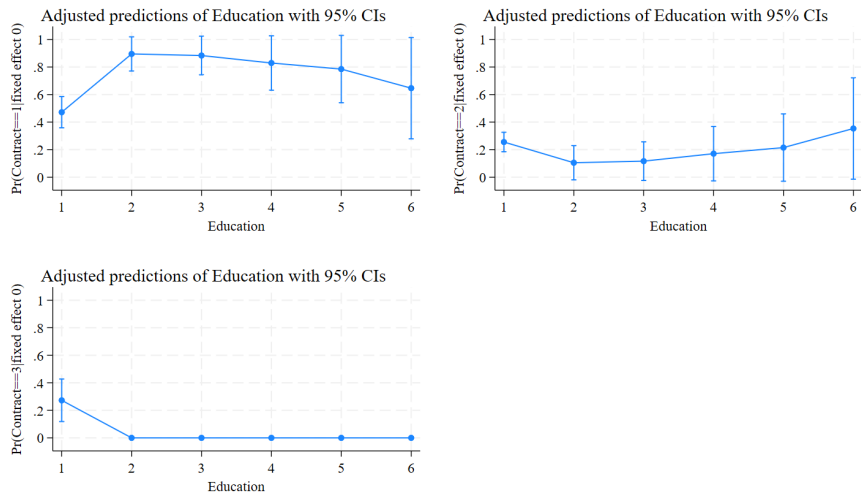


Figure A.14: Margins plot of predicted probabilities of Contract Type by Education attainment.

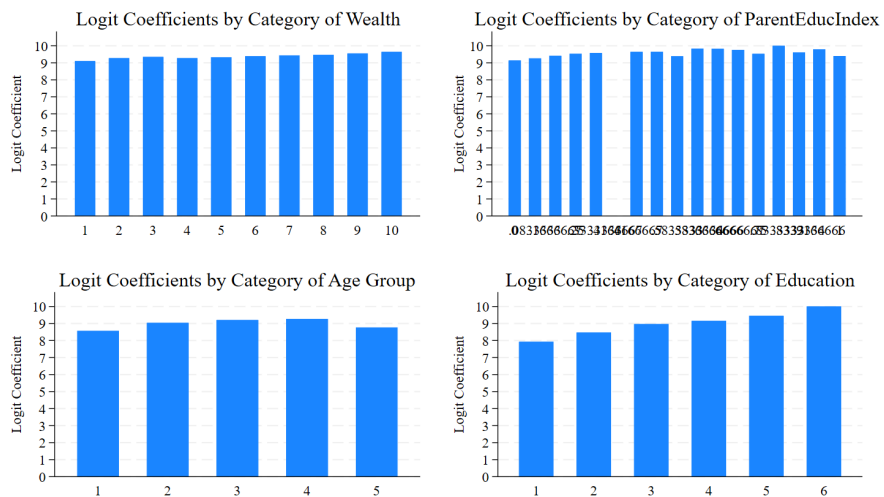


Figure A.15: Linearity of Predictors. Logit coefficients by Category of independent variables. Dependent variable is Part-Time Work.

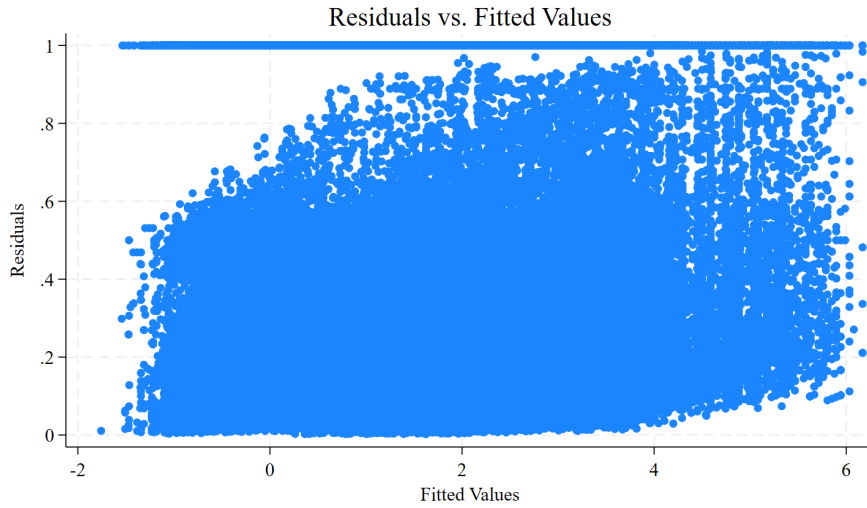


Figure A.16: Homoscedasticity. Residuals against predicted values. Dependent variable is Part-Time Work.

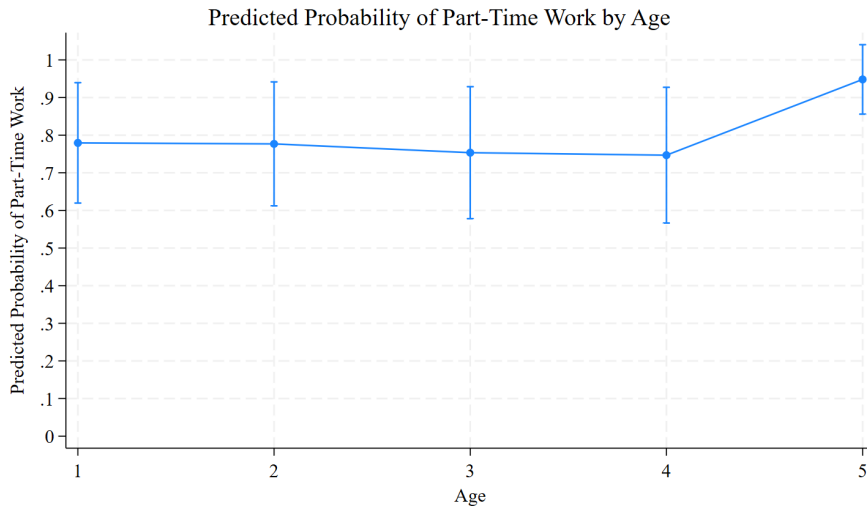


Figure A.17: Margins plot of predicted probabilities by Age Group for Part-Time work.

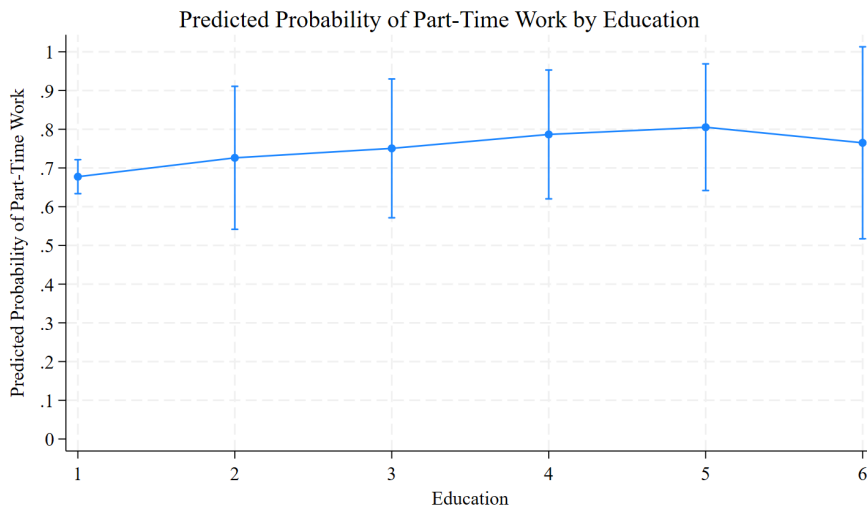


Figure A.18: Margins plot of predicted probabilities by Education for Part-Time work.