Sorting Low-Income Workers*

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Abstract

I study work incentives over the intensive margin of labour by exploring age eligibility rules, housing tenure and deprivation to identify the effects of the Universal Credit welfare system in the UK on low-income workers. Motivated by the descriptive evidence documented in this paper, I examine the discontinuity in the age eligibility cutoff in its relationship with hours of work. Using data from the UK Census 2021 for England and Wales, I estimate *i)* the impact of the increase in income allowance at the age eligibility cutoff and *ii)* the policy boost in the taper rate of the benefits system in November 2021, by implementing a regression discontinuity design and a propensity score matching estimation. The estimates suggest a positive and significant effect on worked hours induced by the increase in income benefits at the age eligibility cutoff and are indicative of sorting of low-income workers into industry sectors. I find a significant treatment effect on treated that raises worked hours in the class 16-30 hours per week and its associated probability by 0.6 percentage points. These findings underscore the importance of in-work progression policies and further income benefits increases that can support low-income workers in moving out from low employment contracts.

Keywords: Labour supply, employment outcomes, Universal Credit, causal inference, regression discontinuity design, propensity score matching
JEL Classification: J18, J21, J22, J38

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1 Introduction

The welfare state in the United Kingdom was modified in 2013 following the Welfare Reform Act 2012 and designed to incorporate all benefits to low-income workers into one single payment to support them pay for living expenses. The aim of the reform was to mitigate income losses and facilitate re-entry into employment. The previous legacy benefits under the UK government consisted of six benefits: housing benefits, income related employment and support allowance, income based job seeker allowance, income support, child tax credit and working tax credit, that were paid separately according to individual characteristics. Using the 2021 UK Census microdata for England and Wales, I document that 31.58% (29.71%) of female (male) low-income workers are on a part time contract working equal or less than 15 hours per week that are eligible for the Universal Credit allowance. This proportion represents a substantial amount of the UK population that poses questions to the government on the efficient allocation of resources.

Moreover, I document important facts that are essential to examine the work incentives of individuals who receive Universal Credit allowances. In the data about 38.67% of female workers are deprived in at least one dimension, while a similar proportion of 39.32% of male workers tend to be deprived in at least one dimension. Furthermore, 36.87% (42.50%) of female (male) workers live in social rented houses, and a significant proportion of 63.18% (57.50%) female workers live in private rented houses, almost double the proportion of workers living in social rented houses. Female low-income workers are more likely to work in the wholesale and retail sector, while male workers dominate the human health and social work industry section with wide disparities at regional level, documented by studying the factors that influence this labour market choice for low-income workers in different industry sectors.

The vast majority of low-income workers living in social rented houses are more likely to be found in the North of England (42.44%), whereas low-income workers living in private rented houses are more likely to be found in the Midlands and East of England (61.52%). The evidence over the life cycle of low-income workers point to a rise in the hours of male workers in the age band 21-26 and a contemporaneous decay in the hours of female workers in the same age class which motivates my analysis on worked hours exploring variations in the age 25 eligibility cutoff. While about 75% of low-income male workers are likely to work on a part time contract between 16-30 hours per week in all industry sectors but wholesale and retail trade sector, transport and food services, and professional and administrative service sector; only 65% of female workers have a part time contract with 16-30 hours a week. In particular, the health and social work sector records 6.6% less female than male workers on the same part time contract.

Two prerequisites for receiving the Universal Credit allowance are that workers need to be in the working age population and must experience a change in their employment and housing status. The programme foresees that at age 25 workers receive a substantial increase in the taper rate. A major boost took place in November 2021 which decreased the taper rate from

63% to 55%. This modification increased the work allowance to £500 yearly. Motivated by this evidence, this paper addresses two questions: Does the increase in income allowance at age 25 increase workers' incentives towards hours of work? Would the November 2021 boost have been an effective policy, had it been applied in March 2021? I investigate these questions on the intensive margin of labour and workers' incentives towards hours of work.

Existing research on the Universal Credit has focussed on understanding the move from the legacy system to the new Universal Credit system and comparing outcomes on mental health (Brewer et al., 2024), as well as on housing insecurity (Williams et al., 2024). I make three main contributions to the literature. First, I evaluate the causal effects of the programme on worked hours by examining exogenous variation of age induced by the presence of the discontinuity at the cutoff. This analysis sheds lights on the labour supply of low-income workers around the age eligibility cutoff. Low-income workers may sort into industry occupations based on their skills and may strategically change the incentive towards hours of work following the rise in the benefits rate. By receiving the allowance, low-income workers may not have an incentive to raise their labour supply, while at the same time they may voluntarily sort into low employment contracts and industry sectors, thereby self-selecting themselves into sectors due to their skills and individual characteristics. Moreover, if the income effect of low-income workers is prevalent, the incentive towards worked hours may be positive. By sorting low-income workers according to industry sectors outcomes, I can examine sorting of the intensive margin of labour of low-income workers.

Second, I estimate the effect of the Universal Credit boost of November 2021 on the intensive margin of labour. In particular, I implement a counterfactual scenario in which the boost is undertaken in March 2021 which is a particular moment in time in which low-income workers were still in receipt of the weekly benefits due to the pandemic. The Universal Credit benefit due to the pandemic expired in October 2021 and therefore, the incentive towards worked hours from low-income workers in March 2021 may have been different than November 2021 when the boost was introduced. Therefore, I contribute by studying the effectiveness of the policy boost in encouraging individuals in receipt of the Universal Credit to increase their hours of work and further progress in their work given the rise in their earnings.

My third contribution is to identify the mechanism surrounding the Universal Credit for the treatment group on the decision to raise worked hours taking into account heterogeneous characteristics of low-income workers. In particular, the probability of raising hours of work may be dependent upon several job specific characteristics concerning the distance to the workplace, the method of transport to the workplace among other features. Furthermore, while on the one hand a married low-income worker may increase worked hours based on a sharing family rule between partners, on the other hand, they can decrease worked hours in the presence of children and significant deprivation in the household. Therefore, the composition of the household can highlight differential treatment effects on low-income workers and indicate a potential driver of the undesired effect on the decision of raising worked hours.

I study the incentive towards worked hours by using variation of the housing tenure and deprivation as a source for identification. In particular, to identify low-income workers in receipt of the Universal Credit I consider individuals living in social rented and private rented houses, who are on a part time contract and that are deprived in at least one dimension, which can be deprivation in education, employment, housing or health. I employ two estimation strategy. First, I estimate a regression discontinuity design exploring variations around age eligibility cutoff at age 25 on the intensive margin of labour for low-income workers close to receiving the increase in the taper rate. This estimation relies on two important assumptions: continuity of the running variable and switching probability of receiving the treatment to the right and left of the cutoff. I show that these two assumptions are satisfied.

Second, I implement a propensity score matching estimator to evaluate the effectiveness of the policy boost on the incentive towards worked hours of low-income workers. To estimate the causal impact of the policy boost, I use information from the programme prior to the boost implementation. In this case, to select a relevant comparison group I use the housing tenure of individuals and therefore, the comparison group is made by low-income workers living in private rented houses that are otherwise similar to the treatment group in all respective individual characteristics except for receiving the treatment. Since low-income workers living in social rented houses are more likely to receive the Universal Credit allowance, they form the treatment group of the analysis.

I find that the age eligibility cutoff leads to a positive effect on worked hours following the rise in the Universal Credit rate that is statistically significant at 1% critical value. While I find conclusive evidence on the intensive margin of labour through a linear polynomial specification, I do not find evidence of impact on worked hours through a local linear regression estimation. I find suggestive evidence that the increase in the income benefits rate at age 25 leads to a change in the housing tenure, deprivation and number of children. I estimate that the age cutoff causes 6.1% increase in the household deprivation that is statistically significant and estimate a small and significant increase in the decision of increasing the number of children by 1 child. Moreover, I find a negative and significant effect on housing tenure which suggests a 3.2 percentage points reduction in housing tenure indicating that low-income workers may be willing to look for other housing alternatives.

My findings are indicative that low-income workers sort into industry sectors. In particular, I estimate a significant reduction in the probability of working in the manufacturing sector equal to 1.8 percentage points, and a significant 9.4 percentage points rise in the probability of working in the wholesale and retail trade sector. I can rule out changes in the hours of work occurring in the transport and food sector and health and social work industry sector since I do not find significant evidence.

In terms of the effectiveness of the Universal Credit boost, the programme accounted for

31.59% of treated individuals and I find a significant treatment effect on treated of 1.897 that consists of an increase in worked hours in the class 16-30 hours per week. I apply different econometric techniques to estimate the parameter of interest, that is the average treatment effect on treated that explore different structural assumptions and conditions.

Analysing the sorting patterns, the results suggest that being treated raises the probability of working in the class of 16-30 hours per week by 0.6 percentage points, thereby being an incentive for low-income workers to find more work and meet programme conditions. By disentangling the effect between workers living in social rented houses and private rented houses, I find that low-income workers living in private rented houses raise the probability of hours of work by 24.29% more than low-income workers living in social rented houses. The probability of raising worked hours for low-income workers living in the private rented houses working in the wholesale and retail sector is estimated to be 54.54% larger than low-income workers living in the social rented houses. Moreover, while I find no evidence of effect of the construction sector on worked hours for individuals living in social rented houses, it delivers a 2.4 percentage points rise in the probability of raising hours in the class 16-30 hours a week for low-income workers living in the private rented houses.

Outline. The rest of the paper proceeds as follows. Section 2 explains the contribution of the paper to the literature. Section 3 describes the data and provides descriptive evidence along different characteristics that motivates the premises of the paper. Section 4 presents the estimation methods of regression discontinuity design and propensity score matching and, details the empirical results for both studies. The analyses are discussed separately. Section 5 discusses the mechanism surrounding the Universal Credit boost on the decision to raise worked hours. Section 6 concludes.

2 Related Literature

This paper relates to the literature that provides evidence on causal estimates of the Universal Credit programme. From a methodological point of view, the paper connects with the literature on regression discontinuity design and propensity score matching estimation by providing evidence that addresses specific features of the programme.

An extensive body of the literature has investigated the impact of low-income worker benefits on labour market outcomes. Card and Levine (2000) study the effect of the extension in the duration of unemployment benefits on the maximum unemployment spells of unemployment insurance claimants. They find a 15% reduction in the rate of leaving the unemployment insurance benefits and a simultaneously rise of 1% to 3% of the fraction of people claiming unemployment benefits at the end of their maximum benefits. Meyer (1990) focusses on a short period prior to the end of the unemployment benefits and finds an increase in the probability of leaving unemployment. Likewise, Katz and Meyer (1990) basing their analysis on recalls of US unemployment insurance claimants find that unemployment spells rise for the people who are not recalled but where expecting the recall. They further confirm Meyer (1990) findings of a rise in the probability of leaving unemployment in the period prior to the end of the unemployment benefits programme.

Lalive (2007) tests the hypothesis that longer periods of unemployment benefits reduce job search incentives by claimants and rise unemployment duration. By testing this hypothesis through a regression discontinuity design of discontinuous rules at age on Austrian unemployment insurance claimants, they find a 4.4% reduction in the fraction of men leaving unemployment after the extension of 170 weeks of unemployment benefits, whereas a much larger effect is found for female with a 53% reduction in the fraction of female leaving unemployment.[1] Similarly to Lalive (2007), Lalive and Zweimüller (2004) study the effect of extensions of unemployment insurance benefits on unemployment duration, however, focussing on the longitudinal aspect of the policy and the endogenous labour market conditions via a triple differences in differences estimation. They find a 17% reduction in the transition rate from unemployment to job, thereby increasing unemployment duration by 9 weeks. Furthermore, they find that omitting the endogeneity of the policy leads to an overestimation of the transition rate with a 40% magnitude.

van Ours and Vodopivec (2006) employ a natural experiment to study the effect of a reduction in the duration of unemployment benefits and find an important positive effect on the probability of finding a job for the claimants subject to the reduction in benefits duration and an improvement effect on the exit rate from unemployment, while the probability of finding a job for people not subject to the shortening of unemployment benefits does not change.

Card et al. (2007) estimates the permanent income hypothesis by investigating the impact of cash on hand versus unemployment benefits extensions on job searcher behaviors. By adopting a quantitative model and a regression discontinuity approach, they find with regards to the former that the behavior of job searchers under cash on hands changes and unemployment benefits are equivalent, and any temporary difference between the two programs is due to liquidity effects. Regarding the latter approach, they find no match quality gains from extending unemployment insurance benefits on wages and job duration.

My paper relates to these studies by examining the impact of a benefits programme such as the Universal Credit in the UK on the intensive margin of labour (hours of work) and differ from the previous studies along two dimensions. First, it studies exogenous variation of age induced by the programme on hours of work and investigates a counterfactual scenario whereby the timing of the implementation of the Universal Credit boost is shifted to pre period actual programme implementation. This counterfactual scenario allows to explore the endogeneity of the policy in a period in which claimants were in receipt of the weekly allowance due to the pandemic as of March 2021.

[1] For a literature review on the extension of unemployment insurance and its effect on unemployment duration via a elasticity measure see Lopes (2022).

Focussing on the importance of benefits on employment, Brewer et al. (2006) employ a structural labour supply model to study working family tax credit of couples, finding that the benefits reduce labour supply of mothers with partner by 0.6 percentage points, but increase the labour supply of fathers with partner by 0.8 percentage points. Evaluating also working family tax credit but on single mothers, Francesconi and van der Klaauw (2007) find a 5 percentage points increase in the employment rate of single mothers with a strong heterogeneous effect for mother with at least one child and no effect for mothers with more than one child. Gregg et al. (2009) consider also single mothers for the impact of in-work tax credit and zoom the implications of these benefits on employment dynamics and hours adjustments. Using a difference in difference estimation, the authors find evidence of an increase in the number of hours of single mothers to 16 hours per week resembling the pattern of worked hours of mothers in couples.[2]

Blundell et al. (2000) and Blundell (2008) examine the effects of the working family tax credit on the incentive to work using a behavioral model of household labour supply and identifying changes in policy reforms that affected the incentive to work of single women. They find an increase in participation rate of single mothers by 2.2 percentage points and a high positive effect on worked hours driven mainly by women who changed jobs.

Recent papers that study the Universal Credit benefits consider different outcomes of investigation. Brewer et al. (2024) explore the impact of the Universal Credit welfare reform in comparison with the previous legacy welfare system on the mental health of unemployed individuals. Using a triple differences in differences estimation, they find an average deterioration of 11.15% standard deviation in single adults and lone parents who are subject to fewer benefits than married parents living in a couple. The effect improves for couples with children reducing mental health problems in these individuals. Exploring the longitudinal feature of the data and individuals trajectories before and after the Universal Credit welfare reform, Williams et al. (2024) implement a difference in differences logistic regression on housing insecurity of claimants living in rented houses. They find a rise in housing insecurity for people entering into the Universal Credit scheme with the effect varying by different types of groups. Thornton and Iacoella (2024) investigate the Universal Credit scheme via a fixed effect regression on life satisfaction and find out that this welfare reform reduces life satisfaction particularly of claimants not in paid work. The impact of the Universal Credit on the social housing sector is investigated in d'Este and Harvey (2024) and find negative incentive effects on housing for individuals located in the bottom of the income distribution.

While examining the exogenous variation induced by age cutoff of the Universal Credit programme, my paper relates to the regression discontinuity analysis of low-income workers on labour market outcomes. Card et al. (2012, 2015a, 2015b, 2017) provide a variant of the regression discontinuity design when the policy function is not differentiable because of the presence of a kink. In this regard, they develop a framework for regression kink design and

[2]Brewer and Hoynes (2019) provide a comparative study of in-work tax credit in the UK and the US, and Blank (2002) reviews the literature on major changes in welfare reforms in the US.

apply it to estimate the duration of unemployment and the elasticity of unemployment benefits duration finding elasticity estimates that are larger than what previous studies indicate. Local polynomial methods for estimation and inference of regression discontinuity design are provided in Imbens and Lemieux (2008) and Lee and Lemieux (2010), with the adequate choice of the local polynomial specification discussed in Calonico et al. (2014, 2020). Recently, Abdulkadıroğlu et al. (2022) generalize regression discontinuity design to allow for a local propensity score to quantify the assignment probability into a school with multiple treatment and running variables. I differ from these studies since I investigate the causal variation around age eligibility cutoff for low-income workers on worked hours.

Propensity score matching methods have been widely applied in the context of causal inference in the labour market. Heckman et al. (1998b) propose to estimate the probability of participating into a programme and then introduce it in propensity score matching estimation. They identify sources of bias coming from selection on unobservable by evaluating the impact of a job training programme and propose a nonparametric conditional difference in differences method for propensity score matching that removes the source of bias. The difference in differences propensity score matching estimation is found to be the most robust method in the context of propensity score (Smith and Todd, 2005). However, the method can be applied when there are temporarily invariant omitted variables that generate bias and when there is a geographical mismatch between the treated participants and control participants. Blundell et al. (2005) estimate the effect of education on earnings via different econometric models, and concerning propensity score matching, they find that this method performs well when estimating the earnings of the treated group. Moreover, a difference in differences propensity score matching estimation for the effects of the New Deal for Young People in the UK delivers an increase of 5 percentage points in the transition to employment (Blundell et al., 2004).

My paper relates to these papers since it explores eligibility rules to identify the effects of the treatment, and second, it differs because tries to estimate the effectiveness of the Universal Credit scheme in a counterfactual scenario designing on a temporal mismatch of implementation of the scheme. In particular, I implement a counterfactual scenario in which the Universal Credit boost of November 2021 is regarded to having been undertaken in March 2021 when economic conditions for low-income workers were more favorable than in November 2021.

3 Descriptive Evidence

This Section describes the data used and provides descriptive evidence that motivates the analysis of the paper.

3.1 Data

I use the UK Census Safeguarded Individual Microdata at regional level in 2021. The dataset is a nationally representative sample of 5% of the UK population. The 2021 UK Census took place the 21 March 2021 and it is a study undertaken every ten years. The sample comprises $3,021,455$ individual respondents and I limit the sample to achieve the scope of this research study. In particular, I keep individual respondents who are economically active in the working age population 16-64, therefore I do not include students and retired respondents. Individual workers are selected as being on a low working hours employment contract working less than 30 hours per week. These contracts are all part-time contracts. Importantly, to fully identify low-income working individuals I consider the housing tenure and therefore, I include individual respondents living in social rented houses, private rented houses and other houses. In the main empirical analysis I further limit the housing tenure variable in the presence of a deprivation indicator to identify the policy effect.

This procedure leaves a sample of $103,650$ individual respondents of which $33,013$ are female and $70,637$ are male individuals respondents. Tables A.3 and A.4 present descriptive evidence of the data according to individual characteristics. The vast majority of the sample consists of individual observation of White race ethnicity of which 63.38% are female and 80.18% are male, followed by Asian, Black, Other and Mixed for female and Black, Asian, Mixed and Other for male.

Since the sample contains low-income workers among them, 31.85% (68.15%) are female working equal or less than 15 (30) hours per week part-time, and 29.71% (70.29%) are male on a part time contract working equal or less than 15 (30) hours per week. Female low-income workers are more likely to have no qualification (22.03%) or a level 4 qualification corresponding to a degree (26.95%). Since these are women on a part time contract this can indicate either that it is a reflexive choice or that they are finding difficult to find a job commensurable to their skills. By contrast, male workers are more likely to have a level 3 qualification corresponding to equal or more than 2 A level (19.56%) or a level 4 qualification corresponding to a degree level with a proportion of 29.06%. Moreover, the data point out that 22.58% and 23.35% of female workers are in the wholesale and retail industry sector and transport and food services industry, respectively. On the other hand, male workers are mainly in the human health and social work industry section with 24.09% proportion, followed by the wholesale and retail sector with 19.63% of male workers.

Furthermore, half of the sample comprises of female workers with two children (34.41%) and no children (21.84%), similarly male workers are more likely to have two children (30.29%) or no children (21.32%), followed by workers having one child aged 16-18 for female (13.05%) and male 13.80%, respectively. Moreover, 63.18% (36.87%) of female workers live in private rented (social rented) houses, and a similar proportion is present for male workers of 57.50% (42.50%) living in private rented (social rented) houses. For both female and male, private rented houses

TABLE 1.—
Racial ethnicity worked hours by regions

	North England			Midlands and East			South England		
	Mean	Obs	Prop. %	Mean	Obs	Prop. %	Mean	Obs	Prop. %
Asian	1.724	2,101	8.239	1.758	670	8.923	1.698	7,631	11.544
Black	1.725	1,126	4.416	1.782	367	4.887	1.699	6,671	10.092
Mixed	1.684	561	2.200	1.712	205	2.730	1.639	2,307	3.490
White	1.728	21,033	82.482	1.716	6,087	81.063	1.677	46,323	70.079
Other	1.652	679	2.663	1.678	180	2.397	1.660	3,169	4.794
Total		25,500	100		7,509	100		66,101	100
Gini			11.574			11.667			12.972

NOTE. This Table presents mean, number of observations and the Gini measure of inequality of worked hours for low-income workers by regions for different race ethnicity in 2021. Data source is the 2021 UK Census microdata.

is the most frequent category with a mean of 1.634 for female and 1.577 for male.

Households are deprived in at least one dimension. Among female 38.67% are no deprived in any dimension, and 41% are deprived in one dimension with 1.857 average frequency of occurrence. Female workers deprived in two and three dimensions account for 16.51% and 3.57% of the sample and 0.25% of them have a deprivation in all four dimensions. Likewise, male workers deprived in one dimension account for 39.32% with 1.577 average mean of occurrence and those no deprived are 45.91% of the sample. These are followed by 12.45% and 2.17% of male deprived in two and three dimensions, respectively and 0.15% are deprived in all four dimensions.

The dimensions of deprivation include education, employment, health and housing. Female workers are more likely to be deprived in the health dimension with a proportion of 29.95%, followed by housing, education and employment with a proportion of 24.01%, 22.64% and 9.13%. Likewise, male are mainly deprived in the health dimension with a proportion of 28.22%, followed by housing, education and employment accounting for 18.31%, 17.91% and 6.91%, respectively. One of the main purpose of the analysis is then to investigate how worked hours varies according to the level of deprivation of each individual respondents.

Appendix A provides further details on the variables. Tables A.1 and A.2 in Appendix A describe the variables used in the descriptive and empirical analyses.

3.2 Racial Worked Hours in the Census

I now present descriptive evidence of hours for low-income workers according to different types of individual characteristics. Table 1 presents evidence on the mean, proportion and a measure of inequality in worked hours by regions. I classify regions in North England which contains the North West, North East, Yorkshire and Humberside; the Midlands and East containing East Midlands, West Midlands and East of England; and South of England comprising London, South

TABLE 2.—
Geographical inequality in worked hours

	Female				Male			
	Mean	Obs	Prop. %	Gini	Mean	Obs	Prop. %	Gini
North East	1.711	1,296	3.926	12.358	1.752	3,114	4.408	10.653
North West	1.706	2,962	12.001	12.176	1.726	8,282	11.725	11.516
Yorkshire and Humb.	1.713	2,634	7.979	11.946	1.730	6,212	8.794	11.376
East Midlands	1.705	2,134	6.464	12.190	1.728	5,375	7.609	11.453
West Midlands	1.707	2,933	8.884	12.121	1.719	6,558	9.284	11.764
East of England	1.655	3,016	9.136	13.649	1.687	7,317	10.359	12.741
London	1.672	8,786	26.614	13.206	1.652	13,293	18.819	13.745
South East	1.647	4,261	12.907	13.854	1.687	10,378	14.692	12.734
South West	1.662	2,651	8.030	13.473	1.710	6,908	9.780	12.039
Wales	1.710	1,340	4.059	12.027	1.751	3,200	4.530	10.693
Total		33,013	100			70,637	100	
Gini, between ineq.				12.908				12.263

NOTE. This Table presents mean, number of observations and the Gini measure of inequality of worked hours between and within geographical regions for low-income workers for each region in the sample. Data source is the 2021 UK Census microdata.

East and South West.

The Table highlights that regardless of region and ethnicity, low-income workers tend to work an average number of work hours between 16 and 30 hours on a part time contract. In the North of England 82.48% of workers are of White ethnicity followed by 8.24% who are Asian ethnicity, with the least present ethnicity being Mixed and constituting 2.2% of the sample observations. Similarly, for Midlands and East regions White (81.063%) and Asian (8.923%) ethnicity are the most recurrent ethnicity, however Other ethnicity is the ethnicity with the lowest affluence. By contrast, low-income workers in the South of England are sorted in White, Asian and Black constituting 70.08%, 11.54% and 10.09%, respectively. Mixed ethnicity remains the ethnicity with the lowest presence in the South of England amounting to 3.49%.

The inequality in hours presents a low coefficient across geographical regions with the largest value 12.972% present for the South of England, which indicates that hours tend to be almost equally distributed across regions.

3.3 Geographical Hours for Low-Income Workers in the Census

In this Section I present descriptive evidence with a spatial perspective on the labour supply of low-income workers and the inequality in the intensive margin across geographical regions. Table 2 presents the proportion for observations of worked hours by gender across regions and the inequality in worked hours between geographical regions and within regions.

The average category of worked hours for low-income workers is working between 16-30 hours per week for both female and male groups. A large proportion of female workers working

TABLE 3.—
Worked hours and housing tenure

	North England			Midlands and East			South England		
	Mean	Obs	Prop. %	Mean	Obs	Prop. %	Mean	Obs	Prop. %
Social rented	1.735	10,751	42.426	1.724	2,857	38.322	1.696	26,299	40.030
Private rented	1.719	14,540	57.491	1.721	4,567	61.517	1.670	39,202	59.849
Total		25,291	100		7,424	100		65,501	100
Gini			11.519			11.648			12.940

NOTE. This Table presents mean, number of observations and the Gini measure of inequality of worked hours for low-income workers given the housing tenure of the individual. Data source is the 2021 UK Census microdata.

on a low hour part time contract are located in London (26.61%), followed by the South East (12.91%) and the North West (12%). A more equal distribution of low-income workers is present for male who appears mainly located in London (13.745), East of England (12.741), South East (12.734) and South West (12.039).

Between regions hours present a Gini coefficient of 12.908% and 12.263% for female and male workers, respectively, indicating that hours continue to be evenly distributed in the category of 16-30 working hours in a part time contract with an almost uniform distribution. Within hours inequality has the largest Gini coefficient of 13.854% in the South East for female workers and 13.745% in London for male workers. Worked hours present the least inequality in Yorkshire and Humberside with 11.946% inequality for female, whereas the North East has the lowest worked hours inequality of 10.653% for male workers.

3.4 Worked Hours by Housing Tenure in the Census

I now examine the prevalence of worked hours given the housing tenure of low-income workers. Living in social rented houses or private rented houses increases the likelihood for individual workers to receive the Universal credit that will be analysed in the next Sections.

Table 3 presents mean, proportion and between inequality of worked hours. Across the three considered regions, working 16-30 hours per week on a part time contract is the likely choice of low-income workers. The proportion of workers living in a social rented house is 42.426%, 38.322% and 40.030% in the North England, Midlands and East of England and the South of England, respectively. Low-income workers in a private rented house accounts for 57.491% in the North of England, 61.517% in the Midlands and East of England, and 59.849% in the South of England.

Between group inequality across social rented and private rented houses of low-income workers remains low and almost resembling a uniform distribution with a Gini coefficient of 11.519% in the North of England, 11.648% in Midlands and the East of England, and 12.940% in the South of England.

Table 4.—
Worked hours in geographical regions along the lifecycle

	North England			Midlands and East			South England		
	Mean	Obs	Prop. %	Mean	Obs	Prop. %	Mean	Obs	Prop. %
16-20	1.676	698	2.737	1.714	245	3.263	1.633	1,723	2.607
21-26	1.699	3,093	12.129	1.709	879	11.706	1.658	6,720	10.166
27-32	1.735	5,066	19.867	1.714	1,434	19.097	1.677	11,311	17.112
33-39	1.735	5,842	22.910	1.725	1,758	23.412	1.687	15,422	23.331
40-44	1.738	3,106	12.180	1.743	963	12.825	1.696	9,614	14.544
45-49	1.733	2,428	9.522	1.747	739	9.842	1.697	7,489	11.330
50-54	1.721	1,985	7.784	1.720	590	7.857	1.682	5,877	8.891
55-59	1.713	1,759	6.898	1.704	503	6.699	1.657	4,419	6.685
60-64	1.697	1,523	5.973	1.688	398	5.300	1.654	3,526	5.334
Total		25,500	100		7,509	100		66,101	100
Gini			11.574			11.667			12.972

Note. This Table presents descriptive statistics of worked hours along the lifecycle for low-income workers across geographical regions. Data source is the 2021 UK Census microdata.

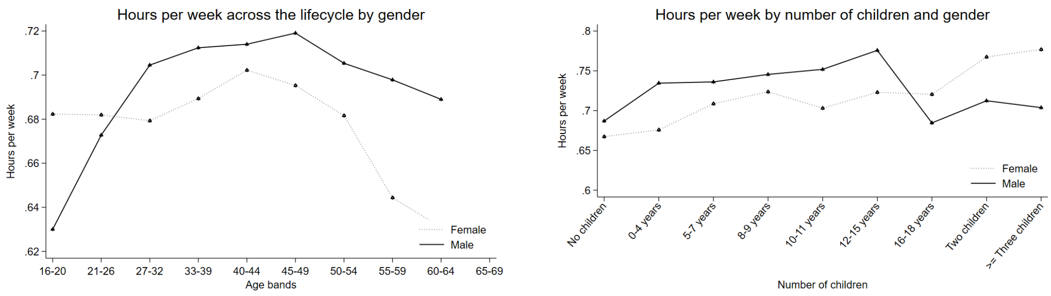
3.5 Worked Hours by Age in the Census

An important indicator to examine the incentive towards the intensive margin of labour is the age of the individual worker and the number of children low-income workers have to take care of caring responsibilities. Table 4 presents mean, number of observations and Gini coefficient of worked hours across geographical regions in England. Part time contracts with 16-30 hours appear the recurrent working pattern across regions. The vast majority of workers undertaking this working pattern are aged 33-39 with 22.910%, 23.412% and 23.331% in the North of England, Midlands and East and South of England, respectively.

This is followed by workers aged 27-32 who represent 19.867% in the North of England, 19.097% in the Midlands and East and 17.112% in the South of England. Low-income workers aged 40-44 constitutes the third dominant category working less than 30 hours per week and amounts to 12.180% in the North of England, 12.825% in the Midlands and East and 14.544% in the South of England.

As there are only two categories were worked hours tend to be evenly distributed amongsts workers, there is low inequality in the number of worked hours with the largest relative inequality in hours present in the South of England with a 12.972% Gini coefficient.

Figure 1 Panel A presents the hours of work for female and male workers over the lifecycle. The hours of work is coded as 0-1 variable taking value 0 for part time contract with less than 15 hours per week and 1 for part time contract with 16-30 hours per week. Therefore, the interpretation of the y-axis goes as any switch in the mean of hours per week and by age between 0-1 represents a change in the number of hours. Panel A shows that from 21 years onward, male workers work more hours than female over all age classes. After reaching age class 50-54 female



(A) Worked hours over the lifecycle (B) Worked hours by no. children

FIG. 1.— The figure shows worked hours per week over the lifecycle and by the number of children. The vertical axis shows mean hours per week for two dummy categories, part time contract with ≤ 15 hours per week and part time contract with 16-30 hours per week. The horizontal axis represents the classification of age bands and number of children, respectively. Data source is the 2021 UK Census microdata.

workers decrease the number of hours of work significantly more than men which is a fall of about 9.375% relative to male workers. Moreover, at age 25-26 in the class band 21-26 it is highlighted an increase in males hours of work and a contemporaneous decay in females hours of work which may have a washing effect in the causal estimates around the age 25 discontinuity which is analysed below in Section 4.1. Therefore, this fact can be informative for the impact of the discontinuity on the average treatment effect.

Figure 1 Panel B presents hours of work for female and male by the number of children. Male workers presents a greater average number of hours than female hours for a given number of children. This is significantly evident when the individual has no children or one children aged from 0-4 years up to 16-18 years. At this age, female workers turn their labour supply increasing it and reflecting the fact that as the child become more independent, low-income female workers can dedicate more time for work. Likewise, when individual workers have two or more children, female workers present a larger average number of worked hours than men indicating that in these occasions, when more than one child is present, female workers feel the need to increase their work to meet childcare costs.

3.6 Deprivation in Low-Income Workers

This Section establishes the presence of household deprivation in the data, Table 5 presents worked hours by household deprivation. In particular, it considers whether the household is not deprived in any dimension, and if it is deprived, there are four dimensions of deprivation: education, employment, health and housing. A household can be deprived in one to four dimensions. If a household is deprived in all four dimensions I include them in household deprived in three dimensions.

The Table shows that a great proportion of low-income workers is deprived in at least one dimension. In North England 39.650% of low-income workers are on a part time contract working

TABLE 5.—
Worked hours by household deprivation

	North England			Midlands and East			South England		
	Mean	Obs	Prop. %	Mean	Obs	Prop. %	Mean	Obs	Prop. %
No deprived	1.750	11,408	45.107	1.742	3,279	44.168	1.697	28,023	42.783
One dimen.	1.712	10,028	39.650	1.716	2,931	39.480	1.675	23,223	40.035
Two dimens.	1.693	3,195	12.633	1.687	1,008	13.578	1.653	9,370	14.305
Three dimens.	1.682	660	2.609	1.632	206	2.775	1.639	1,885	2.878
Total		25,291	100		7,424	100		65,501	100
Gini			11.519			11.648			12.940

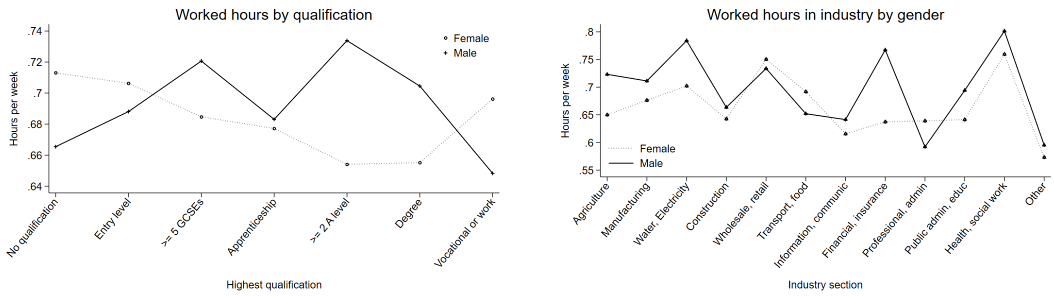
NOTE. This Table presents mean, number of observations and the Gini measure of inequality of worked hours for low-income workers by the presence of deprivation in the three regions considered. Data source is the 2021 UK Census microdata.

16-30 hours per week deprived in one dimension. Likewise, 39.480% and 40.035% of low-income workers in Midlands and East, and the South of England, respectively, are deprived in one dimension working on a part time contract. Low-income workers deprived in two dimensions constitute 12.633%, 13.578% and 14.305% of the workforce in North England, Midlands and East, and South of England. While there is a small percentage of workers deprived in three dimensions, their presence is not without consideration as they represent 2.609%, 2.775% and 2.878% in the North, Midlands and East, and the South of England, respectively.

The South of England records the largest inequality in worked hours (12.940%) relative to the North of England (11.519%) and Midlands and East (11.648%) indicating a more uniform distribution of hours.

Figure 2 Panel A presents worked hours by the highest qualification of the worker by gender which constitutes one dimension of deprivation. Hours per week is a two-category variable between 0-1 for hours less than 15 hours on a part time contract and between 16-30 hours part time contract. Female workers without qualification and entry level as well as with vocational qualification show a larger incentive towards worked hours than male workers. For all other categories $\geq$ 5 GCSEs level, apprenticeship, $\geq$ 2 A level and degree level, male workers have an average number of worked hours that is consistently larger than the mean hours of female low-income workers.

Panel B shows the average worked hours between female and male according to the industry section. Female workers tend to work an average number of worked hours larger than male workers in sectors such as wholesale and retail trade, as well as transport and food services, and professional and administrative services. In all other industry sectors, about 75% of low-income male workers are likely to work on a part time contract with hours between 16-30 hours per week. Given the same industry sectors, only 65% of female workers have a part time contract with 16-30 hours per week. In the health and social work sector, there are 6.66% less female than male workers on the same part time contract. Likewise, the financial and insurance sector



(A) Worked hours by highest qualification

(B) Worked hours by industry

FIG. 2.—The figure shows worked hours per week for each highest qualification considered and gender. The vertical axis shows mean hours per week for two dummy categories, part time contract with ≤ 15 hours per week and part time contract with 16-30 hours per week. The horizontal axis represents the classification of highest qualification. Data source is the 2021 UK Census microdata.

records 18.75% less female than male workers on a part time contract with less than 30 hours per week.

4 Empirical Evidence

This Section examines the impact of the Universal Credit on low-income workers. It addresses two important questions. First, it examines whether the increase of the Universal Credit rate at age 25 changes workers' incentives towards hours. Second, it investigates whether boosts to the Universal Credit payments make a difference to low-income workers, specifically, whether the Universal Credit boost of November 2021 had been an effective policy if it had been applied in March 2021. I tackle these questions with a different methodology for both questions aimed at addressing them. The former question is examined through a regression discontinuity design, the latter is addressed via a propensity score matching estimation.

Section 4.2 explains the identifying assumptions, Section 4.1 and Section 4.4 describe the theoretical methods, whereas Section 4.3 and Section 4.5 show the empirical results. Appendix B provides detailed information on the Universal Credit scheme.

4.1 Regression Discontinuity Design of Age on Worked Hours

In this Section I present the econometric specification. I implement a regression discontinuity design in its sharp version to study the increase in the Universal credit rate at age 25. My primary outcome variable is the incentive towards working hours. Sharp regression discontinuity design implies that the assignment of individuals to the treatment is not random, but is fully determined by the cutoff age and the values of hours worked—the outcome variable—to the left or to the right of the cutoff.

The treatment is the rise in the Universal Credit rate at age 25 and the continuous running variable is age of the individual worker. I obtain casual identification since individuals above and below the age cutoff 25 are similar in all observable characteristics except for the treatment. With the rise occurring at age 25 individual workers may have a disincentive to increase their hours of work, therefore I would expect a fall in worked hours from low-income workers. Furthermore, low-income workers may sort into low hours contract voluntarily as they strategically decide their labour input in the presence of a rise in income allowance. By contrast, if the income effect is prevalent individuals workers may still choose to work more and increase their hours of work to meet end. It is normally received in the literature that low-income workers tend to have a positive substitution effect. Since assignment to the treatment is not completely random, if the rise in the Universal Credit rate affects the probability of a worker to increase their worked hours it will then impact their earnings and conditions set out in the Universal Credit individual scheme.

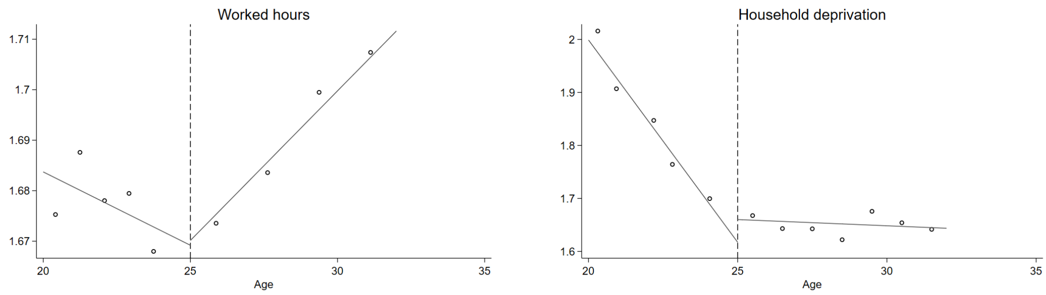
Assuming continuity of all individual characteristics, except for age at the treatment cutoff, the sharp regression discontinuity estimates the average treatment effect of changing worked hours for an individual with age equal to the cutoff age. I use local linear regression within a given bandwidth of the treatment threshold and control for age on each side of the threshold as suggested by Imbens and Lemieux (2008) and Gelman and Lemieux (2019). Therefore, I estimate the following specification:

$$\text{hours}_i = \beta_0 + \beta_1 \mathbb{1}\left\{age_i \geq C\right\} + \beta_2(age_i - C) + \beta_3(age_i - C)\mathbb{1}\left\{age_i \geq C\right\} + \mu X_i + \epsilon_i, \quad (1)$$

$$Y_i = \gamma_0 + \gamma_1 \text{hours}_i + \gamma_2(age_i - C) + \gamma_3(age_i - C)\mathbb{1}\left\{age_i \geq C\right\} + \zeta X_i + \eta_i, \quad (2)$$

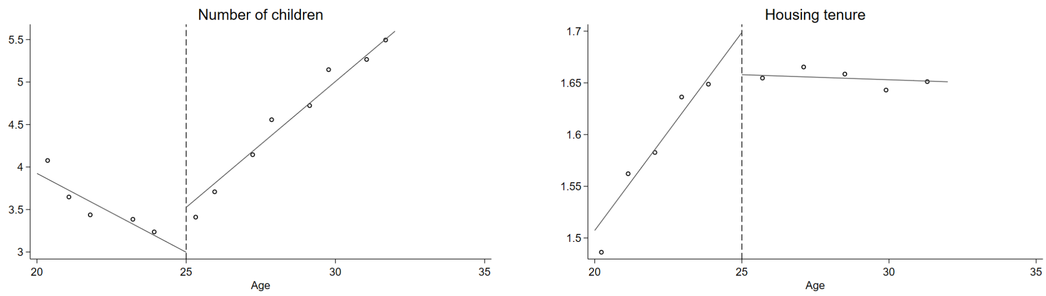
where, Y_i is the outcome variable of interest for individual i, C is the cutoff threshold on age, age_i is the running variable age, X_i is a vector of individual characteristics which include a set of dummies for some variables, ϵ_i and η_i are the error terms in the specifications. Controls in the vector X_i include covariates for economic activity, employment status, ethnicity group, number of dependent children, household deprivation in any dimension which include employment, education, health and housing, the highest level of qualification, country of birth, marital status, industry sector, occupation, place of work, distance to travel to work, gender, size of the household and housing tenure.

The variable hours_i is a categorical variable taking value 1 if the individual workers changed the working hours, and 0 if individual worker did not change work hours. In the analysis hours is also a categorical variable with value 1 indicating the workers work between 16-30 hours per week, and 0 when the individual workers works less than 15 hours per week, both on a part time contract. I do not include fixed effect in the estimation since they are not necessary in this case, although they can improve the efficiency of the estimation. The coefficient β_1 identifies treated individuals, and β_2 how close to the threshold the individual is, β_3 is the coefficient measuring the interaction between treated and distance to the threshold. The coefficient γ_1 gives the estimated impact of hours and age on the outcome variable.



(A) Worked hours per week (B) Household deprivation

FIG. 3.—The figure plots means across bins over individual characteristics. Vertical line specifies the age threshold at age 25. A linear fit is generated separately for each variable to the right and to the left of the cutoff. Bins are selected evenly spaced with uniform Kernel. Each point consists of around 1,300 observations. The sample is made of low-income individuals on a part time contract. Data source is the 2021 UK Census microdata.

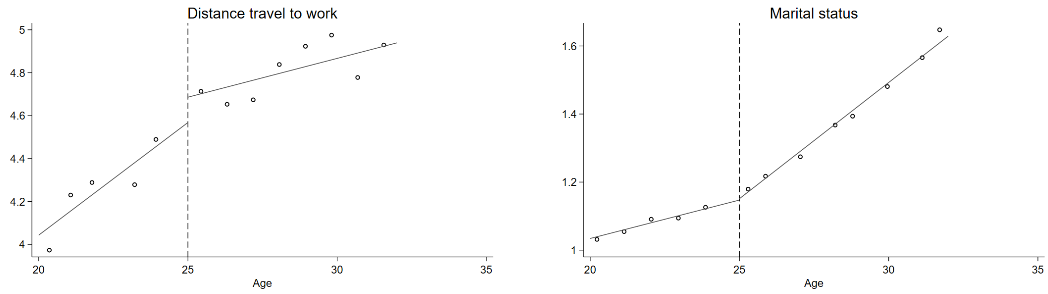


(A) Number of children (B) Housing tenure

FIG. 4.—The figure plots means across bins over individual characteristics. Vertical line specifies the age threshold at age 25. A linear fit is generated separately for each variable to the right and to the left of the cutoff. Bins are selected evenly spaced with uniform Kernel. Each point consists of around 1,300 observations. The sample is made of low-income individuals on a part time contract. Data source is the 2021 UK Census microdata.

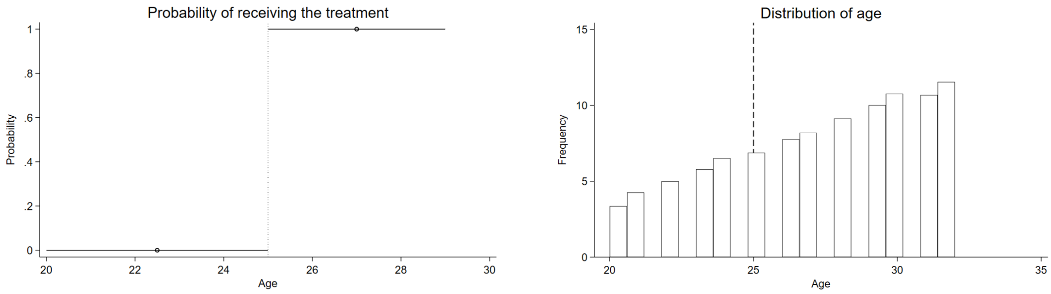
The optimal bandwidth is selected via mean squared error with the optimal bandwidth being 2.45 or selected manually. I follow Dell (2015) and Asher and Novosad (2020) and use a triangular kernel instead of a rectangular kernel since this allows to give more weights to the observations close to the threshold. For a given outcome variable, results are similar with different choice of controls and different bandwidth.

Regression discontinuity design can provide causal interpretation if the control variables are continuous at the threshold and have a reasonable balance to the right and left of the cutoff threshold. Figure 3, 4 and 5 show the means of variables in population bins and shows that controls are continuous at the threshold and designate the presence of a cutoff at age 25. Figure 6 Panel B shows the density of the individual age distribution which is also continuous at the treatment cutoff and does not show spurious spikes. Panel A shows the probability of receiving the treatment which switches around the cutoff of the running variable.



(A) Distance travel to work (B) Marital status

FIG. 5.—The figure plots means across bins over individual characteristics. Vertical line specifies the age threshold at age 25. A linear fit is generated separately for each variable to the right and to the left of the cutoff. Bins are selected evenly spaced with uniform Kernel. Each point consists of around 1,300 observations. The sample is made of low-income individuals on a part time contract. Data source is the 2021 UK Census microdata.



(A) Probability of receiving treatment (B) Histogram of distribution of running variable

FIG. 6.—Panel A shows the probability of receiving the treatment as function of the threshold. Panel B shows the distribution of age around the age cutoff. The vertical dotted line identifies the age threshold for receiving the rate increase. Data source is the 2021 UK Census microdata.

4.2 Identifying Assumptions and the Evaluation of Empirical Strategy

To assess the impact of the rise of the Universal Credit rate at age 25 I impose limit on age and therefore, I include in the sample individuals aged 20-32 years. Since this policy is specified for low-income workers, I use the housing tenure and deprivation controls to identify affected workers. This means that I consider individuals living in social rented houses and private rented houses only, and that are deprived in at least one dimension.

The incentive towards hours of work depend on different factors some of which are endogeneous to hours and therefore, a regression of worked hours on age only may lead to biased estimates. I implement a regression discontinuity design to investigate quasi-experimental variation around the threshold to examine the causal effect of the threshold age on hours worked and a set of other outcome variables. I interpret the setting as a situation in which, holding constant all other factors that can influence the outcome variable at the threshold, the presence of a cutoff indicates that age has a causal effects on worked hours.

Since sharp regression discontinuity design is a data driven procedure, it relies on two fundamental assumptions: continuity of the outcome variable in the absence and presence of the treatment to the right and to the left of the cutoff, and the probability of receiving the treatment must switch to the right and left of the cutoff.

Figure 6 shows that both assumptions are satisfied and no spikes are present in the running variable. Furthermore, outcome variables and control variables appear to be continuous at the threshold. There are enough observations to the right and to the left of the cutoff consisting of $23,274$ and $7,740$ observations, respectively.

The sharp regression discontinuity estimates the average treatment effect on treated that is $\mathbb{E}(\gamma_1|C) = \mathbb{E}(\gamma_1|C^+) - \mathbb{E}(\gamma_1|C^-)$ which is identified in a neighborhood of the C cutoff in the presence of a discontinuous function. In the non parametric estimation, the regression discontinuity fits a local weighted linear regression at the boundary point on both sides of the threshold which is particularly sensitive to the choice of the bandwidth. I take into account this aspect of the procedure in the next Section.

4.3 Results on the Regression Discontinuity Analysis

I begin by presenting the treatment estimates on worked hours. Table 6 presents the regression discontinuity estimates of the impact of age cutoff on worked hours aimed at addressing whether the increase in the Universal Credit rate at age 25 and its discontinuity change work incentives towards hours of low-income workers. I report estimates in the parametric specification testing for the discontinuity and the fully local linear regression.

The first two columns show a positive effect of age on worked hours which is statistically significant at 1% critical value in both specifications with and without the inclusion of all regressors. The estimated effect on worked hours equals to 0.8% and while small, is economically important. The linear specifications support the presence of a discontinuity at the age cutoff, which suggests that the increase in the Universal Credit rate at age 25 raises worked hours of low-income workers. By contrast, a polynomial specification in its quadratic version rejects the presence of the discontinuity with no significant impact on worked hours, however it highlights a discontinuity in squared age that is significant at 5% critical value. In the non parametric specification, the results show a positive sign impact of age on worked hours, however they do not reject the null hypothesis of zero effect on worked hours. Low-income workers may not change hours of work at age 25 following the increase in the Universal Credit rate, as one possible hypothesis is to delay the speed at which low-income workers exit the Universal Credit scheme.

Table 7 shows regression discontinuity estimates of the impact effect of age cutoff on different outcome variables which include industry sector, deprivation index, the number of children, and the housing tenure. The estimates are presented for the baseline specification with mean squared error bandwidth and alternative choices of the bandwidth as well as in the discontinuity sample with $+5/-5$ band sample. The results corroborates the early findings that the increase in income rate at the threshold age 25 leads to a change in the work incentives towards hours. The

TABLE 6.—
Effect of age on worked hours treatment

	Parametric				Non Parametric	
	Linear	Linear, full	Quadratic	Quadrat., full	LLR	LLR, full
Treated	-0.163	-0.009	-0.002	0.003		
	(0.010)	(0.0013)	(0.130)	(0.017)		
Age	0.005***	0.008***	-0.0246	-0.014	0.012	0.013
	(0.001)	(0.001)	(0.0158)	(0.021)	(0.025)	(0.025)
Age squared			0.001**	0.0004		
			(0.0003)	(0.000)		
Constant	1.566***	1.492***	1.961***	1.788***		
	(0.029)	(0.038)	(0.213)	(0.267)		
R^2	0.0007	0.009	0.0008	0.010		
RMSE	0.463	0.457	0.463	0.457		
No. obs.	31,014	20,962	31,014	20,962	31,014	31,014

NOTE. This Table presents coefficient estimates on hours of work and different outcomes at different age cutoff. Columns identified with full include a set of regressors specified in the main text. LLR stands for local linear regression computed within a given bandwidth. Robust standard errors are reported in parentheses. *, **, *** indicate p-values at 1%, 5% and 10%, respectively. Data source is the 2021 UK Census microdata.

age cutoff causes a 6.1% increase in the household deprivation which is statistically significant at 5% critical level. This result is robust to different choices of the bandwidth and discontinuity sample around the cutoff.

The impact on the number of children is four times greater than on the household deprivation effect, leading to a rise in the decision of increasing the number of children by 0.282 in the household. The effect on housing tenure is negative and statistically significant resulting in a 3.2% reduction in social rented houses potentially suggesting that individual workers may opt for a better housing alternative.

The estimated impact effect on industry, while positive is not statistically significant as low-income workers may sort into industry occupations based on their skills and can leverage the rise in the income rate of the Universal Credit more strategically. In Table 8 I examine how the increase in the income rate at the age cutoff changes incentives towards hours in industry sectors. The results estimate a 1.8% reduction in the probability of working in the manufacturing sector which is statistically significant and robust to alternative choice of the bandwidth.

Likewise, the estimated effect on wholesale and retail trade shows a 9.4% rise in the probability of working in this sector following an increase in the income rate at the threshold. The results for transport and food services, and health and social work indicate a positive impact effect on the probability of working more in these sectors, however the results for both sectors are not statistically significant. This is in part due to the largest presence of observations in the manufacturing and wholesale and retail trade sectors accounting for most of the estimated impact effect of the cutoff.

TABLE 7.—
Regression discontinuity estimates on different outcomes

	Industry				Deprivation			
	Baseline	Bandw. 4	Bandw. 5	Disc.	Baseline	Bandw. 4	Bandw. 5	Disc
Age	0.042	0.084	0.068	0.068	0.066	0.061**	0.057**	0.057**
	(0.155)	(0.116)	(0.098)	(0.098)	(0.045)	(0.033)	(0.028)	(0.028)
No. obs.	31,014	31,014	31,014	24,114	30,642	30,642	30,642	23,790
	No. children				Housing tenure			
	Baseline	Bandw. 4	Bandw. 5	Disc.	Baseline	Bandw. 4	Bandw. 5	Disc.
Age	0.318	0.248	0.282**	0.282**	-0.017	-0.029	-0.032**	0.035
	(0.210)	(0.154)	(0.131)	(0.131)	(0.026)	(0.019)	(0.017)	(0.031)
No. obs.	20,962	20,962	31,014	15,684	30,642	30,642	30,642	23,790

NOTE. This Table presents regression discontinuity estimates on different outcome variables. The first column is the baseline specification, bandw. specifies the bandwidth chosen above and below the cutoff. Disc represents the discontinuity sample with $+5/-5$ band in the age threshold. Triangular kernel is computed in the estimation. Robust standard errors are reported in parentheses. *, **, *** indicate p-values at 1%, 5% and 10%, respectively. Data source is the 2021 UK Census microdata.

4.4 Propensity Score Matching and the Universal Credit 2021 Boost

In this Section I examine the causal impact of the Universal Credit programme boost of November 2021 on worked hours by addressing the question of whether this policy would have been an effective boost if it had been carried out in March 2021.

My approach to estimate the impact of the rise of Universal Credit allowance is to use information from the programme prior to the boost implementation. This boost can affect the hours of work of both treated and control group in different ways. Treated individuals may increase their job efforts in raising hours of work to meet the conditions set out in the Universal Credit programme since any acceptance to the programme is normally monitored. However, other individuals may reduce their incentive towards working more hours via a free riding problem.

Therefore, there could be a rise in employment from low-income workers and at the same time a reduction in the intensive margin of labour from the same workers. The extent of both effects depends on the attractiveness and substitutability of these workers in the labour market. Since these workers tend to be less skilled individuals, the increase in their search for better jobs with more prospects for hours can reduce the prevailing wage and, employment through more part time contracts with less than 30 hours per week may rise for both treated and non treated individuals.

I assess the substitution effects by using information on the housing tenure of the individuals since Universal Credit allowances are more likely to be granted to workers living in social rented houses who are separate from individuals living in private rented houses. The choice of the comparison group is therefore of crucial importance. I examine the propensity score matching

TABLE 8.—
Sorting low-income workers

	Manufacturing			Wholesale and retail trade		
	Baseline	Bandw. 4	Bandw. 5	Baseline	Bandw. 4	Bandw. 5
Age	-0.018**	-0.015**	-0.012**	0.094***	-0.003	-0.003
	(0.009)	(0.007)	(0.006)	(0.010)	(0.017)	(0.015)
No. obs.	31,014	31,014	31,014	31,014	31,014	31,014
	Transport and food			Health and social work		
	Baseline	Bandw. 4	Bandw. 5	Baseline	Bandw. 4	Bandw. 5
Age	0.001	0.006	0.006	0.017	0.021	0.016
	(0.021)	(0.015)	(0.013)	(0.021)	(0.016)	(0.013)
No. obs.	31,014	31,014	31,014	31,014	31,014	31,014

NOTE. This Table presents regression discontinuity estimates over industry sectors. The first column is the baseline specification, bandw. specifies the bandwidth chosen above and below the cutoff. Triangular kernel is computed in the estimation. Robust standard errors are reported in parentheses. *, **, *** indicates p-values at 1%, 5% and 10%, respectively. Data source is the 2021 UK Census microdata.

in this scenario following the insights of Heckman and Robb (1985), Heckman et al. (1998b), Heckman et al. (1996), Heckman et al. (1998a).

Let assume Y_i^1 and Y_i^0 be the outcome for individual i who are exposed and non exposed to the policy rise implementation, respectively. Define by UCB the treatment of receiving the Universal Credit Boost, then the average treatment effect on treated is $\mathbb{E}(Y_i^1 - Y_i^0 | \text{UCB} = 1)$. The fundamental problem of causal inference which is present in any evaluation problem specified under the Rubin (2005) causal model poses the impossibility to observe the outcome for the treated individuals had they not received the treatment, and likewise for control individuals only one outcome is observable.[3]

To specify the comparison group, first I define the treatment group as individuals under the Universal Credit programme who receive the boost, live in social rented houses, are on a part time contract and can be deprived from one to four dimensions which include deprivation in education, employment, health and housing. Since my outcome variable is the hours of work, I then contrast the intensive margin of labour with the housing tenure of the individuals. This means that the comparison group is made of workers on part time contracts who live in a private rented houses and can be deprived from one to four dimensions, hence they are comparable to the treatment group in all respective individual characteristics. Therefore, UCB $= 1$ and UCB $= 0$ designate whether the individual lives in social rented or private rented houses, under the assumption that the hours of work for both types of individuals are the same in the absence of the policy boost. The average treatment effect on treated estimator can then be written as ATT $= \mathbb{E}(Y_i^1 | D = 1) - \mathbb{E}(Y_i^0 | \text{UCB} = 1) = \mathbb{E}(Y_i^1 - Y_i^0 | \text{UCB} = 1, \text{Prob}(\text{UCB} = 1 | X) < 1)$, whereby comparing the hours of work between social rented and private rented housing individuals measures the impact

[3] A detailed literature review on propensity score matching is available in Caliendo and Kopeinig (2008).

of the Universal Credit boost on treated individuals.

Under the conditional independence assumption, outcomes must be independent from the treatment given observable characteristics implying that the conditional distributions of the treated individuals in the absence of the treatment are the same of the control individuals (Rosenbaum and Rubin, 1983). Moreover, the probability of receiving the treatment given observable characteristics must be bounded, $0 < \text{Prob}(\text{UCB} = 1|X) < 1$. Randomization then occurs by aligning the distributions of the treated individuals with the distributions of the control individuals when the program is active.

I explore the housing tenure of the individual as a metric for eligibility to have the Universal Credit and then obtain the boost. In particular, $\text{UCB} = 0$ represents all those individuals who are similar to the treated individuals in all individuals characteristics except for receiving the treatment because of the eligibility over the housing tenure. Therefore, the behavior of the hours of work for both groups in the absence of the program is likely to be the similar, providing the counterfactual for the treated individuals without the policy boost treatment. This allows me to retrieve how much the individual receiving the treatment benefited compared to a case they would have not received the treatment and in a different moment in time when participants where receiving an additional income allowance per week due to the pandemic. The disadvantage can be that treated individuals may increase hours work more than control individuals by virtue of substitution, however if the needs of labour for both groups are equivalent without the policy implementation then the two groups should be comparable.

To account for the impact of heterogeneous observable characteristics, propensity score matching allows to create a matched sample of the treated population with the untreated population that ascertains that the distribution of observable characteristics for both groups are the same. Denoting with $P_{\text{UCB}} = \text{Prob}(\text{UCB} = 1|X)$ the propensity scores of treated individuals, then the distributions of observable characteristics between treated and control groups must be balanced, that is:

$$\mathbb{E}(Y_i^0|P_{\text{UCB}}, \text{UCB} = 1) = \mathbb{E}(Y_i^0|P_{\text{UCB}}, \text{UCB} = 0). \tag{3}$$

The parameter of interest is then obtained as the propensity score conditional on the treatment over the difference in outcomes for treated and control individuals. The propensity scores are then estimated parametrically and non parametrically.

I estimate the following specification:

$$Y_i = \lambda_{\text{UCB}} + \beta_1 X_i + \beta_2 \text{UCB}_i + \epsilon_i, \tag{4}$$

where Y_i is the outcome variable of worked hours which indicates whether the individual is in a part time contract working less than 15 hours per week or in a part time contract working between 16-30 hours per week, λ_{UCB} is the intercept on treated individuals, β_2 measures the average difference between the treated and control group, X_i is the vector of observable characteristics

Table 9.—

Propensity score matching sample

	Sample	Treated	Untreated
No. obs.	$44,557$	$14,075$	$30,482$
Proportion, %	100	31.59	68.41

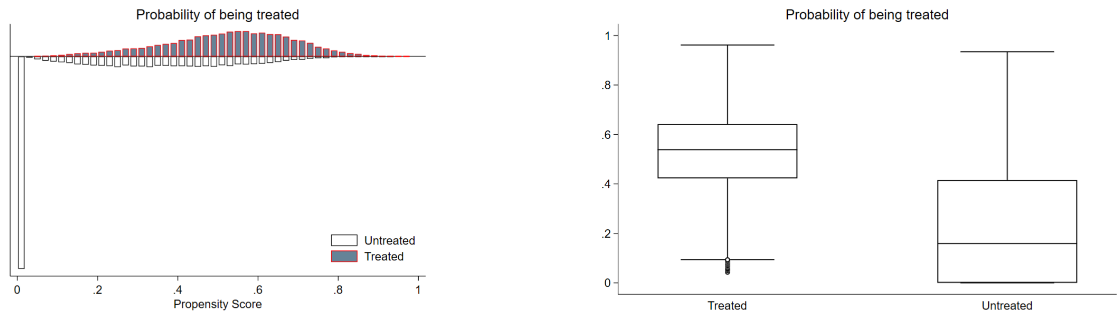
Note. This Table presents the sample size and proportion once the comparison group has been chosen adequately. Data source is the 2021 UK Census microdata.

with vector of coefficients β_1, and ϵ_i is the error term of the estimation. I choose predictors so as to maximise the in sample matching, hence they include: age of the individual, dummies for economic activity, employment status, ethnicity group, number of dependent children, household deprivation in any dimension which include employment, education, health and housing, the highest level of qualification, country of birth, dummies for marital status, industry sector, occupation, place of work, distance to travel to work and size of the household.

I then estimate probit models of participation into the Universal Credit programme for treated individuals. Treated individuals are in working age population 18-64 to be eligible for the treatment. The time in which the boost of the Universal Credit was implemented in November 2021 is of particular importance since this is a time in which the weekly allowance due to the pandemic was removed. The incentive towards hours of work following the boost of the programme is influenced by these factors. In March 2021 low-income workers on a Universal Credit scheme were still in receipt of the income allowance due to the pandemic and therefore, their propensity towards working more hours might have been substantially different than when the boost occurred in November 2021.

The source of the bias is normally addressed with propensity score matching by performing matching over the common support and reweighting control units with treated units. Any source of the bias would then be attributed to differences in unobservable characteristics. To reduce the curse of dimensionality I implement Mahalanobis-metric matching which reduces differences in observable characteristics of matched individual units by assigning a weight to each predictor in proportion to the inverse of the variance of predictors. Matching can be performed with neighborhood or weights. I implement four types of matching algorithms to evaluate the Universal Credit boost: Nearest Neighborhood, Caliper matching, Kernel matching, One to one matching and Regression adjusted local linear matching, which differ in the choice of the weights and neighborhood.

Nearest Neighborhood methods can be performed in one-to-one matching or k-nearest neighborhood matching with and without replacement. They distinguish themselves for matching an individual in the comparison group with a treated individual on the basis of a close propensity score. While nearest neighborhood without replacement requires complete randomisation of the order of the variables since it is sensitive to it, nearest neighborhood with replacement faces a bias variance trade-off since the more information obtained with replacements improves the



(A) Distribution score probability of treated

(B) Box plot of probability being treated

FIG. 7.—Panel A shows the probability of being treated in common support of the distribution of the score. Panel B shows the respective box plot of the propensity score for the probability of receiving the treatment. The vertical dotted line identifies the age threshold for receiving the rate increase. Data source is the 2021 UK Census microdata.

quality of matching reducing the bias, however if matches are not of high quality there can be an increase in the bias.

Caliper matching allows to impose a tolerance to the distance of the unit with the propensity score. Therefore, an individual comparison unit to be matched with a treated unit needs to be within the bounds of the propensity scores chosen with the caliper tolerance level. The method still face a bias variance trade-off since the quality of the matches increases by including matches in the bounds and removing poor matches which in turn reduces the bias, but lower matches can increase the variance.

Kernel matching is a nonparametric matching estimator that attributes a weight to non treated units in proportion to the closeness of the outcome of the treated unit with the non treated unit. Weights can take several forms as using all non treated units like in the Gaussian kernel, or some of the units on a rolling window over the comparison group such as tricube weights, bi-weights or Epanechnikov kernel weights. In practice, more weight is given to the control units close to the treated units given the propensity score and viceversa, thereby reducing the variance given the availability of more information to choose the comparison group. Kernel matching is sensible to the choice of the bandwidth which is relevant to determine the closeness of the non treated unit to the treated unit given the propensity score. It is subject to the bias variance trade-off and its choice needs to be balanced for a small variance and the necessity of obtaining unbiased estimates.

Likewise, local linear matching as nonparametric matching estimator relies on the choice of the bandwidth to obtain an acceptable level of bias variance trade-off. However, differently from kernel matching it is part of the local polynomial matching estimators and constructs the propensity score of the treated individuals with the inclusion of a linear term apart from the intercept. Both estimators need to fulfill the common support assumption and ensure that only the units of the control group close to the treated units in terms of observable characteristics are included for the avoidance of any source of bias.

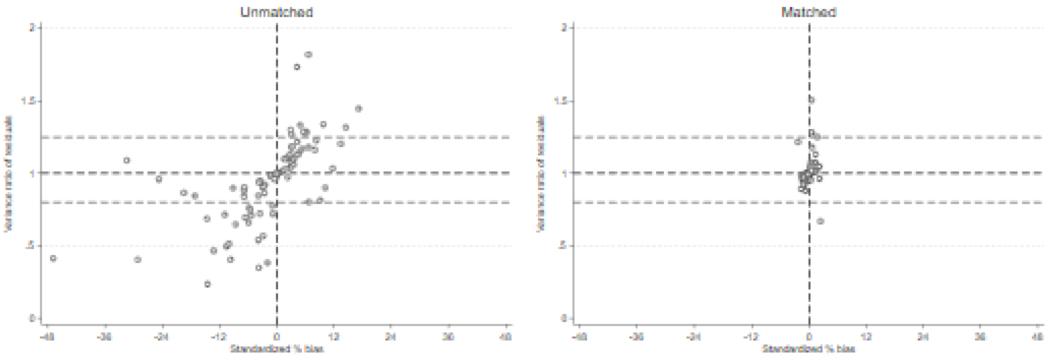


Fig. 8.—Probability of being treated in nearest neighborhood

Note. The figure shows the variance ratio for matched and unmatched sample with nearest neighborhood without replacement and without caliper matching of the propensity score matching estimation. Data source is the 2021 UK Census microdata.

4.5 Results on the Propensity Score Matching Analysis

I now present the estimated results of the propensity score matching on hours of work. Table 9 indicates that 31.59% of the sample is made up of treated units and 68.41% of control units. Figure 7 studies the common support assumptions through the distribution of the predicted propensity score and the alternative box plot of the propensity score. While some outliers are evidenced in the distribution of the treated probability, the two distributions prior to implementing matching are misaligned, and the average propensity score of the distribution of treated individuals is approximately 55% compared to the 19% of the propensity score of untreated individual units.

Table 10 shows the results of the propensity score matching estimation under parametric and non parametric estimation. I use a probit regression to estimate the propensity score representing the probability of receiving the Universal Credit boost given the individual observable characteristics. All estimators considered are consistent in terms of estimating an average treatment effect on treated that is 1.897, which represents a 1.897 increase in the number of hours of treated individuals in the class of 16-30 hours per week.

The difference in means is small and statistically significant only under the nearest neighborhood propensity estimation without replacement and without Caliper matching. Under this method, untreated individuals are chosen only once as a match and since the order of the variables matters, it needs to be completely random. Nearest neighborhood with replacement involves a bias variance trade-off due to more information used to construct the counterfactual which can result in an increased bias although the matching quality of the estimates rises. While the matching quality is good for all estimation methods considered, I present the quality of the matching only under the estimation which delivers a statistically significant average treatment effect on treated and controls.

Since the difference in treated and control estimates is small I perform analysis on the covariates balance. Tables 11 and 12 show the matching quality of the estimated impact for

TABLE 10.—
Impact of the programme boost on average treatment effect on treated

	Treated	Controls	Difference	Ratio impact effect
Nearest neighborhood with replacement	1.897	1.894	0.002 (0.006)	1.001
Caliper matching	1.897	1.894	0.002 (0.006)	1.001
Nearest neighborhood without replacement, no Caliper	1.897	1.889	0.007* (0.004)	1.004
Nearest neighborhood without replacement, with Caliper	1.892	1.891	0.0002 (0.005)	1.000
One to one matching	1.897	1.902	-0.005 (0.004)	0.997
Kernel matching, band 0.06	1.897	1.901	-0.004 (0.004)	0.998
Kernel matching, band 0.01	1.897	1.901	-0.004 (0.004)	0.998
Kernel matching, band 0.10	1.897	1.899	-0.003 (0.004)	0.999
Mahalanobis metric matching	1.897	1.893	0.003 (0.005)	1.002
Abadie and Imbens in Mahalanobis	1.897	1.893	0.003 (0.005)	1.002

NOTE. This Table presents results of the average treatment effect on treated on worked hours of the Universal Credit boost. Treated units are individuals in the working age 18-64, living in social rented houses and deprived in at least one dimension. The ratio of impact effect is the ratio between treated and control results. Parenthesis indicate standard errors on the difference in outcomes of hours. Data source is the 2021 UK Census microdata.

each regressor with nearest neighborhood without replacement and without Caliper matching. Treated individuals are matched to control individuals based on similarity of the propensity scores. The results show that the model does well in matching treated and control units since all predictors show a statistically significant average treatment effect on treated on unmatched individual units. The bias of common support arises since there are cases in which treated and control units do not overlap, however once matching is performed the bias is reduced. The regressor age shows a substantial reduction in bias of 80.6% in the matched sample. The variance ratio in the Table reports the ratio between treated and control individuals. The sign * on this statistic, indicates whether the matching is of concern or is bad. The former requires the variance ratio to be between $[0.8, 0.8)$ and $(1.25, 2]$, the latter occurs when the variance ratio is < 0.5 or > 2. All predictors show a well balanced matching since the ratio for the treated matched sample is 1 or very close to 1, which is confirmed in the quality of the matched individuals, with the exception of some predictors such as ethnicity black and marital status in a civil partnership

Table 11.—

Impact of the programme boost on matching

Variable	Treated	Control	% Bias	% Bias reduction	Variance ratio
Age					
Unmatched	38.322***	37.051***	11.7		1.03
Matched	37.785	38.031	-2.3	80.6	1.22
Ethnicity White					
Unmatched	0.719**	0.709**	2.2		0.97
Matched	0.743	0.744	-0.4	82.9	1.00
Ethnicity Black					
Unmatched	0.120***	0.071***	17.2		1.45*
Matched	0.080	0.080	0.3	98.4	1.01*
Married					
Unmatched	0.317***	0.399***	-17.2		0.84
Matched	0.352	0.354	-0.3	98.0	1.00
In civil partners.					
Unmatched	0.002***	0.003***	-2.9		0.57*
Matched	0.002	0.002	0.2	92.2	1.05*
Level 2 qualif.					
Unmatched	0.175***	0.123***	14.4		1.32*
Matched	0.163	0.165	-0.6	96.2	0.99
Children aged 0-4					
Unmatched	0.079***	0.112***			0.72*
Matched	0.097	0.093	1.2	89.2	1.03
Children aged 5-7					
Unmatched	0.040	0.041	-0.3		0.98
Matched	0.047	0.045	0.9	-242.4	1.04
Place of work, not home					
Unmatched	0.721***	0.674***	10.1		0.90
Matched	0.705	0.706	-0.2	97.8	1.00
Transport bus					
Unmatched	0.128	0.125	0.7		1.01
Matched	0.112	0.113	0.1	89.5	1.00
Industry, manufacturing					
Unmatched	0.026***	0.038***	-6.6		0.70*
Matched	0.030	0.031	0.4	94.0	1.02
Industry, wholesale retail					
Unmatched	0.231	0.236	-1.3		0.98
Matched	0.231	0.227	1.0	20.1	1.01
Depriv. education					
Unmatched	0.246***	0.334***	-19.5		0.87
Matched	0.257	0.250	1.5	92.3	1.01

Note. This Table presents results of the average treatment effect on treated for the Universal Credit boost with Nearest Neighborhood without replacement and without Caliper matching. Variance ratio is the variance of treated over control. Significance for equality in means treated and control is ***$p< 0.01$, **$p< 0.05$ and *$p< 0.10$ critical values. **$v(< 0.5, > 2)$ and *$v[0.5, 0.8)|(1.25, 2]$ in variance ratio indicates a ratio of bad and of concern, respectively. Data source is the 2021 UK Census microdata.

TABLE 12.—

Impact of the programme boost

Variable	Treated	Control	% Bias	% Bias reduction	Variance ratio
Depriv. housing					
Unmatched	0.299***	0.417***	-24.8		0.96
Matched	0.269	0.267	0.4	98.4	1.01
Depriv. health					
Unmatched	0.405***	0.560***	-31.5		1.09
Matched	0.429	0.434	-1.0	97.0	0.99
Depriv. employm.					
Unmatched	0.050	0.202	-46.8		0.41**
Matched	0.044	0.048	-1.2	97.4	0.93
Social position					
Unmatched	3.111***	3.027***	9.1		0.81
Matched	3.017	3.014	0.4	95.5	0.96
Size household, 2					
Unmatched	0.303	0.297	1.4		1.02
Matched	0.314	0.309	1.2	13.5	1.01
Size household, 3					
Unmatched	0.202***	0.188***	3.5		1.06
Matched	0.212	0.213	-0.3	90.1	0.99
Size household, 5					
Unmatched	0.156*	0.149*	1.9		1.03
Matched	0.139	0.143	-1.0	47.9	0.98
Occupation					
Unmatched	76.243***	74.629***	6.7		0.80
Matched	74.825	74.288	2.2	66.7	0.96
Pseudo R^2					
Unmatched	0.308				
Matched	0.001				
LR χ^2					
Unmatched	$13,871.45$***				
Matched	36.03				
Bias in means					
Unmatched	6.9				
Matched	0.7				
Rubin B					
Unmatched	123.1*				
Matched	9.1				
Rubin R					
Unmatched	0.01*				
Matched	0.90				

NOTE. This Table presents results of the average treatment effect on treated for the Universal Credit boost with Nearest Neighborhood without replacement and without Caliper matching. Variance ratio is the variance of treated over control. Significance for equality in means is ***p$<$ 0.01, **p$<$ 0.05 and *p$<$ 0.10 critical values. **v($< 0.5, > 2$) and *v$[0.5, 0.8)|(1.25, 2]$ in variance ratio indicates a ratio of bad and of concern, respectively. Data source is the 2021 UK Census microdata.

which both show a ratio of variance of concern for the matched sample.

Figure 8 shows the variance of the residuals in terms of the standardised percent bias. The regressors in the matched sample fall within the band of variance ratio with the exception of two regressors that fall in the larger band of the variance ratio. Figure C.1 in Appendix C demonstrates that the quality of the matching before and after matching of the covariates occurs between treated and control units. The propensity score matching of treated and control units achieves an almost equal balance between the two groups with an average probability of being treated equal to 0.50, relative to the unmatched covariates counterpart.

Examining the importance of the estimates of the regressors, the pseudo R^2 shows that before matching regressors are good predictors of the assignment of the treatment since it equals 0.308 indicating the presence of lack of balance between treated and control units. However, after matching the pseudo R^2 drastically reduces to 0.001 which further shows that regressors are not anymore contributing to the assignment of the treatment and therefore, balance between treated and control units is reached. I take this evidence as successful matching of the propensity score between treated and control individual units.

The result is corroborated by the Likelihood Ratio test which does not reject the null hypothesis of good balance between treated and control units after matching. The average bias in means between covariates of treated and control units significantly reduces once matching occurs, although some improvement can be made by re-choosing covariates. The standardised difference in means of treated and control units measured through the Rubin B points toward a significant reduction in bias to 0.9 which is less than 25 demonstrating that the matching process has reached a good balance in covariates. The variance ratio of covariates in the Rubin R equals 0.90 that is in the range of suggested variance $(0.8, 1.25)$, confirming the good balance of the matching. Altogether these estimates show that regressors have been balanced well by the matching process.

Tables C.1 and C.2 in Appendix C provide the results of the propensity score estimation by using Mahalanobis metric distance matching. This procedure highlights that matching have been successful along few individual characteristics such as: marital status in civil partnership where estimates for treated and control are significant for unmatched individuals and the bias of non overlap significantly reduces by 100% with an in line variance ratio of 1 indicating that the predictor does not contribute anymore to the matching. Likewise, families with children aged 0-4, industry manufacturing, social position, size of the household with three individuals and occupation show a successful matching since matched estimates for treated and control individuals are insignificant and show a strong reduction in bias. While lack of balance is confirmed before matching with a 0.308 pseudo R^2 similarly to the nearest neighborhood without replacement and caliper, after matching it is not completely removed and still lies at 0.18. Moreover, the Likelihood Ratio test rejects the null hypothesis of good balance between predictors which indicates that in this setting Mahalanobis metric matching distance may not be the appropriate

TABLE 13.—

Estimates of marginal effects probit estimation on worked hours

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	0.007***	0.007***	0.006**	0.005*	0.005*	0.005**	0.006**	0.006**	0.005*	0.005*	0.005*	0.005**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age	0.014***	0.015***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asian		0.009**	0.009**	0.009**	0.010**	0.009**	0.009**	0.008*	0.009**	0.009**	0.009**	0.005
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Married		-0.010***	-0.010***	-0.008***	0.010***	-0.008***	-0.008***	-0.008***	-0.009***	-0.009***	−0.009***	-0.009***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Entry qualif.			0.005	0.009***	0.010***	0.009***	0.009**	0.009***	0.008**	0.007**	0.008**	0.008**
			(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\geq$ 5 GCSEs			0.008**	0.013***	0.013***	0.012***	0.012***	0.012***	0.011***	0.011***	0.011***	0.011***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Vocational				0.020***	0.020***	0.021***	0.021***	0.020***	0.019***	0.019***	0.019***	0.021***
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
No fixed workplace				-0.035***	-0.034***	-0.034***	-0.033***	-0.033***	-0.033***	-0.030***	-0.028***	-0.032***
				(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Transport, train					-0.007	-0.007	-0.007	-0.007	-0.005	-0.004	-0.006	-0.007
					(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Transport, bus					0.008**	0.008**	0.008**	0.008**	0.009**	0.007***	0.006	0.007*
					(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Manufacturing						0.017**	0.018***	0.018**	0.018**	0.018**	0.017**	0.014*
						(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Construction						0.016***	0.017***	0.016***	0.015**	0.015**	0.015**	0.005
						(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Wholesale, retail						0.017***	0.019***	0.019***	0.018***	0.018***	0.018***	0.016***
						(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Social position							-0.002*	-0.002*	-0.003**	-0.003**	-0.003**	-0.003***
							(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size hh, 3 people								-0.011***	-0.011***	-0.011***	-0.011***	-0.007**
								(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Accommodation type									-0.007***	-0.007***	-0.007***	-0.007***
									(0.001)	(0.001)	(0.001)	(0.001)
2-5km work travel										0.012***	0.014***	0.014***
										(0.004)	(0.004)	(0.003)
10-20km work travel											0.013***	0.012***
											(0.005)	(0.005)
Female												0.021***
												(0.003)
Pseudo R^2	0.256	0.256	0.256	0.261	0.261	0.262	0.261	0.261	0.262	0.263	0.263	0.264
Number obs.	44,557	44,557	44,557	44,557	44,557	44,557	43,867	43,867	43,867	43,867	43,867	43,867

NOTE. Marginal effects of the Universal Credit on worked hours for all sample of individuals. Robust standard errors are reported in parenthesis. Significance is ***p< 0.01, **p< 0.05 and *p< 0.10 critical values. Data source is the UK Census microdata.

procedure of analysis.

Figure C.2 in Appendix C presents the quality of the matching through the variance ratio of covariates and shows that after matching all regressors but one are within the range of the variance ratio, which adds to the small drop of the pseudo R^2 in delivering a good matching.

The explanation on nearest neighborhood without replacement and without caliper performing better than Mahalanobis metric distance matching relies on the types of covariates, the majority of which are dummies and therefore nearest neighborhood method is able to estimate treatment assignment probability taking into account the specificity of the covariates. Consequently, matching occurs in the space of the propensity score balancing each dummy and categorical variable with their predicted probability. This type of regressors may not have any influential impact under the Mahalanobis metric distance matching and can vanish in the matrix of variance distance, thereby reducing the quality of the matching.

The results suggest that while matching have been successful in balancing covariates for population comparisons removing problems of misspecification, the effect of the Universal Credit boost in 2021 would have be small had it been applied in March 2021 since all methods agree on the same effect on worked hours of treated individuals with very small differences in comparison to the control individuals. Furthermore, the results corroborates the hypothesis of targeting resources more effectively.

5 Mechanism

In this Section I study the sorting mechanism that arises under the Universal Credit scheme. In particular, I control for heterogeneous characteristics that can affect the incentive towards the intensive margin of labour to identify low-income workers who benefit and those who do not benefit according to different individual classes such as: household composition, distance to travel to work, education, geography patterns, place of work, and industry sectors.

In the analysis low-income workers are on a flexible working arrangement working on a part time contract between 0-30 hours a week. Since hours of work is coded as a categorical variable, I consider the two relevant working patterns of working between 0-15 hours a week and 16-30 hours a week. A simple regression over worked hours may bias the estimates upward or downward with the direction of the bias dependent on the type of the coefficient. Therefore, I code the variable hours of work as a dummy variable taking value 0 if the individual is working 0-15 hours and 1 if the individual is working 16-30 hours a week. I then investigate the mechanism that leads to a change in the probability of working more hours through a probit estimation. I study this mechanism for the whole sample of low-income workers and then separately for individuals living in social rented houses and private rented houses.

Table 13 show the estimated results for all sample of workers. The results suggest that across all specifications being treated and receiving the Universal Credit allowance raise the

TABLE 14.—

Estimates of marginal effects probit estimation on worked hours for social rented houses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asian		0.003	0.003	0.004	0.004	0.004	0.003	0.003	0.005	0.005	0.005	-0.004
		(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Married		0.000	-0.000	0.000	0.000	0.000	-0.001	-0.002	-0.002	-0.002	-0.002	-0.007
		0.005	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Entry qualif.			-0.007*	-0.001	-0.001	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
			(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\geq$ 5 GCSEs			0.004	0.009*	0.009*	0.009*	0.007	0.007	0.007	0.007	0.007	0.007
			(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Vocational				0.019***	0.019***	0.021***	0.018***	0.018***	0.018***	0.018***	0.018***	0.021***
				(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
No fixed workplace				-0.028***	-0.028***	-0.026***	-0.024***	-0.024***	-0.024***	-0.022***	-0.021***	-0.025***
				(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Transport, train					-0.004	-0.004	-0.003	-0.003	-0.000	0.001	-0.001	-0.005
					(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
Transport, bus					0.002	0.002	0.002	0.002	0.004	0.002	0.002	0.004
					(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Manufacturing						0.016	0.018	0.018	0.017	0.018	0.017	0.017
						(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)
Construction						0.004	0.005	0.004	0.004	0.004	0.004	-0.007
						(0.009)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
Wholesale, retail						0.013***	0.016***	0.015***	0.015***	0.015***	0.015***	0.011**
						(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Social position							-0.008***	-0.007***	-0.008***	-0.008***	-0.008***	-0.011***
							(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	0.002
Size hh, 3 people								-0.013***	-0.012***	-0.012***	-0.012***	-0.009*
								(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Accommodation type									-0.009***	-0.009***	-0.009***	-0.006***
									(0.002)	(0.002)	(0.002)	(0.002)
2-5km work travel										0.008*	0.011**	0.012**
										(0.005)	(0.005)	(0.005)
10-20km work travel											0.015**	0.017**
											(0.007)	(0.008)
Children aged 0-4												-0.024***
												(0.006)
Female												0.029***
												(0.005)
Pseudo R^2	0.274	0.274	0.274	0.277	0.277	0.278	0.278	0.278	0.280	0.280	0.280	0.265
Number obs.	21,220	21,220	21,220	21,220	21,220	21,220	20,750	20,750	20,750	20,750	20,750	17,558

NOTE. Marginal effects of the Universal Credit on worked hours for individuals living in social rented houses. Robust standard errors are reported in parenthesis. Significance is ***p< 0.01, **p< 0.05 and *p< 0.10 critical values. Data source is the UK Census microdata.

Table 15.—

Estimates of marginal effects probit estimation on worked hours for private rented houses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age	0.015***	0.015***	0.015***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asian		0.013**	0.013**	0.013**	0.013**	0.011*	0.011*	0.010*	0.011*	0.012**	0.012*	0.005
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Married		-0.016***	-0.015***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.013***	-0.012***	-0.012***	-0.014***
		(0.005)	(0.004)	0.004	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Entry qualif.			0.017***	0.021***	0.021***	0.019***	0.019***	0.019***	0.018***	0.018***	0.018***	0.014**
			(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\geq$ 5 GCSEs			0.011**	0.015***	0.015***	0.014**	0.013**	0.014**	0.012**	0.012**	0.012**	0.012*
			(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Vocational				0.019***	0.019***	0.021***	0.021***	0.021***	0.019***	0.019***	0.019***	0.017***
				(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
No fixed workplace				-0.040***	-0.040***	-0.040***	-0.040***	-0.040***	-0.041***	-0.037***	-0.036***	-0.038***
				(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Transport, train					-0.011	-0.011	-0.011	-0.011	-0.009	-0.008	-0.011	-0.016
					(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)
Transport, bus					0.014***	0.014***	0.014**	0.013**	0.014***	0.011**	0.011*	0.014**
					(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Manufacturing						0.017*	0.018*	0.018*	0.017*	0.017*	0.017*	0.018
						(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Construction						0.025***	0.025***	0.024***	0.023***	0.023***	0.023***	0.017
						(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)
Wholesale, retail						0.021***	0.021***	0.021***	0.021***	0.021***	0.021***	0.017***
						(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Social position							-0.000	-0.000	-0.000	-0.001	-0.001	-0.004*
							(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Size hh, 3 people								-0.007	-0.007	-0.007	-0.007	0.001
								(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Accommodation type									-0.006***	-0.006***	-0.006***	-0.006***
									(0.001)	(0.001)	(0.001)	(0.002)
2-5km work travel										0.017***	0.018***	0.015***
										(0.005)	(0.006)	(0.006)
10-20km work travel											0.011	0.012
											(0.007)	(0.008)
Children aged 0-4												-0.024***
												(0.006)
Female												0.026***
												(0.005)
Pseudo R^2	0.240	0.241	0.242	0.247	0.247	0.248	0.247	0.248	0.248	0.249	0.249	0.243
Number obs.	23,337	23,337	23,337	23,337	23,337	23,337	23,117	23,117	23,117	23,117	23,117	18,519

Note. Marginal effects of the Universal Credit on worked hours for individuals living in private rented houses. Robust standard errors are reported in parenthesis. Significance is ***$p < 0.01$, **$p < 0.05$ and *$p < 0.10$ critical values. Data source is the UK Census microdata.

probability of working between 16-30 hours per week by an average of 0.6 percentage points. Therefore, the rise in the Universal Credit rate appears to be an incentive for low-income workers to find more work. By contrast, being married reduces the probability of increasing the number of worked hours for low-income workers by an average of 0.9 percentage points. The estimates are all statistically significant. To examine the education level, I consider levels of qualifications that are more relevant to low-income workers such as low entry qualifications, $\geq$ 5 GCSEs and vocational qualifications. Among the educational levels considered, low-income workers with vocational qualification gain the most from receiving the benefits. In particular, low-income workers with vocational qualifications experience a statistically significant 2 percentage points probability of increasing hours of work, which is 53.85% larger than the probability facing low-income workers with $\geq$ 5 GCSEs level qualifications.

Low-income workers without a fixed place of work have the hardest difficulty of raising the probability of increasing hours of work in the class 16-30 hours per week, which is estimated to decline by 3.3 percentage points and is statistically significant at 1% critical value. Sorting low-income workers under the Universal Credit scheme in industry sectors, workers in the manufacturing sector and the wholesale and retail sector have a relatively higher propensity to increase the probability of working more hours than workers in the construction sector, that is a statistically significant 5.88% increase.

While the method of transport by train to the place of work does not have a statistically and significant effect, travelling by bus raises the probability of working more hours in the vast majority of the cases by 0.8 percentage points that is statistically significant at 5% critical value. The distance to the place of work has a prominent role on the probability of raising worked hours consequently to the Universal Credit boost. Living between 2km and 20km away from the place of work has a positive impact on the probability of increasing worked hours in the 16-30 class hours per week with an effect ranging from 1.2 to 1.4 percentage points. The social position of the worker and the size of the household, have both a negative effect on worked hours suppressing the probability of working more hours by 0.3 percentage points for the former control and by 1.1 percentage points for the latter control variable, with the estimated effects being statistically significant at 1% critical value.

Table 14 presents the estimates for the mechanism considering separately low-income workers living in social rented houses. The age of the worker has a statistically significant positive impact on the probability of working more hours with a 1.3 percentage points rise. Having a vocational qualification and working in the wholesale and retail sector increase the likelihood of raising worked hours by 1.8 and 1.5 percentage points, respectively. Likewise, the lack of a fixed workplace, the social position and the size of the household maintain a consistent negative effect on worked hours. These variables are estimated to reduce the probability of working more hours, by 2.4, 0.8 and 1.2 percentage points, respectively. Travelling 10-20km to the workplace, raise the probability of working 16-30 hours per week by 41.67% relative to the 2-5km distance from the workplace, that is strongly statistically significant. Lastly, having a child aged 0-4 years reduces also the likelihood of working more hours despite the Universal Credit boost by 2.4 percentage points.

Table 15 performs the mechanism on low-income workers living in private rented houses. The estimates corroborate the findings of the previous two analyses. Relative to workers living in social rented houses, low-income workers living in private rented houses experience a 24.29% rise in the probability of raising worked hours. Likewise, being married has a negative and statistically significant effect on worked hours of about 1.4 percentages points, while this effect is insignificant for workers living in social rented houses. Focussing on the full specification, working in the wholesale and retail sector raises the probability of working more hours by 54.54% relative to workers living in social rented houses.

A work travel of 2-5km raises the same probability by 25% relative to workers living in social rented houses. Moreover, the construction sector appears to have relevance for workers living in private rented houses with an estimated increase in the probability of working more hours of 2.4 percentage points, whereas having a child aged 0-4 years has the same statistically significant effect on worked hours of low-income workers living in social rented houses. The absence of a fixed workplace contributes negatively to the probability of raising hours of work especially for low-income workers living in private rented houses. In particular, this group of workers are estimated to obtain a 2.52% larger reduction in the probability under study, than low-income workers living in private rented houses.

These findings suggest that job specific features like industry sector, the distance to the workplace, the social position, the method of transport to the workplace, and individual drivers of the workers like the size of the household, and the age of children in the family analysed in this paper explain an important part of the mechanism that leads low-income workers to change worked hours.

6 Conclusion

This paper has examined the employment impact on worked hours of the Universal Credit scheme. The Universal Credit benefits system is based on eligibility rules and changes in employment as well as housing status. Two aspects of the system are analysed in this paper. First, I explore exogenous variation in age eligibility cutoff at age 25 where low-income workers receive an increase in the income rate allowance, by analysing the causal impact of age eligibility cutoff on worked hours. Second, I evaluate the effectiveness of the Universal Credit boost of November 2021 in a counterfactual experiment had the programme boost been introduced in March 2021, using variation in housing tenure and household deprivation as a source for identification. Third, I study the mechanism by which low-income workers have an incentive to change worked hours.

I find a statistically significant effect on worked hours driven by the increase in income rate at the age eligibility cutoff, although the effect is small. The results indicate that the increase in the income rate at age 25 leads to changes in the housing tenure, deprivation and decision of the number of children. My findings capture a sorting pattern of low-income workers. In particular, my estimates suggest that at the age eligibility cutoff there is a reduction in the probability of working in the manufacturing sector equal to 1.8 percentage points, and a significant 9.4 percentage points rise in the probability of working in the wholesale and retail trade sector.

My estimates point to a positive effect of the average treatment effect on treated, whereby the Universal Credit boost increased hours of work in the class 16-30 hours per week. I estimate that receiving the increase in the income rate raises the probability of working in the class of 16-30 hours per week by 0.6 percentage points. The larger effect is present for low-income workers living in private rented houses where, I estimate the probability to be 24.29% larger than low-income workers living in social rented house. Moreover, the estimates suggest that for individuals in private rented houses working in the wholesale and retail sector experience an increase in the probability of working more hours that is 54.54% larger than individuals in social rented houses and working in the same sector.

I do not estimate the impact of the policy boost and its spillover effects to other regions which I leave for future research. Further research on this aspect would be valuable as it would shed lights on in-work progression of low-income workers and would need to take into account the longitudinal aspect of a different type of data. This is an important next step informed by the findings of this paper that I aim to perform and will also allow me to uncover how robust the estimates are given the economic effects by which the labour decisions of low-income workers are influenced.

As the efficient allocation of resources is one of the primary goals of policymakers, this paper suggests that the age at which low-income workers receive an increase in their benefits as part of the Universal Credit system, as well as the time of the boost implementation of the benefits system are important to obtain positive effects on the intensive margin of labour of low-income workers. Since these workers contribute more to the economy through the rise in their hours of work, this analysis underscores the importance of in-work progression programme, training, further income benefits increases tailored to low-income workers that can support them in moving out from low employment contracts and raise their income by progressing in their work.

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Appendix to
Sorting Low-Income Workers

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A Additional Descriptive Evidence

This Section provides more details on the data and further descriptive statistics.

A.1 Data Details

Tables A.1 and A.2 present a description of the variables used in the analysis. Moreover, I create categories for variables not listed in the Tables. In particular, the variable country of birth contains the following created categories: the UK, Europe consisting of ten categories, Africa which comprises individuals born in Nigeria, South Africa and the rest of Africa, China, Bangladesh, India, Pakistan and all other Asia, Canada, United States, Jamaica, and the rest of United States, and lastly, Antarctica, Oceania and Other countries.

I sort twenty categories for race ethnicity into five groups: Asian, Black, Mixed, White and Other ethnicity. The variable region contains regions of England and Wales. They are North East, North West, Yorkshire and Humberside, East Midlands, West Midlands, East of England, London, South East, South West and Wales. I classify dependent children in family in categories and I create categories for no children in family, one dependent children aged 0-4 years, one dependent children aged 5-7 years, one dependent children aged 8-9 years, one dependent children aged 10-11 years, one dependent children aged 12-15 years, one dependent children aged 16-18 years, two dependent children group which contains individual with youngest children aged 0-4 years up to 16-18 years, three or more dependent children group which comprises individuals with youngest children aged 0-4 to 16-18 years.

The variable industry is classified in 12 categories and individuals are grouped in one of the following categories: *i)* agriculture, forestry and fishing and mining, *ii)* manufacturing, *iii)* electricity and air conditioning supply and water supply, *iv)* construction, *v)* wholesale and retail trade, *vi)* transport and storage, accommodation and food services, *vii)* information and communication, *viii)* financial, insurance and real estate activities, *ix)* professional, scientific and technical activities, administrative and support services activities, *x)* public administration, defence, social security and education, *xi)* health and social work, *xii)* arts, entertainment, recreation, and other services activities.

I use the socio economic status variable for the household and consider in the first category employers in large establishment, higher managerial and administrative occupations and higher professional occupations, the second group contains lower professional and higher technical occupations, lower managerial and administrative occupations. In the third category I include higher supervisory occupations, intermediate occupations employers in small establishments and own accounts workers, in the fourth category I consider lower supervisory and technical occupations. The last category contains individuals in semi-routine and routine occupations. I exclude long-term unemployed and full time students from the analysis.

The housing tenure is of significant importance in the analysis as it helps to uncover low-income workers along with the intensive margin of work. Therefore, I remove individuals who owns a house outright or with a mortgage or loan or with a shared ownership. I sort housing tenure in two categories which are social rented and private rented. The group social rented include individuals renting from council or local authority, other social rented houses and rent free, whereas private rented include individuals renting a house from private landlord or letting agency, employer or relative or friend of a household member, and other types of housing rents.

The majority of two classes categorical variables are transformed in dummy variables with each category taking value 1 if the given instance occurs and 0, otherwise. The main dummies are then included in the analysis.

Table A.3 and Table A.4 present summary statistics on the main variables of the study.

Table A.1.—
Description of variables used

Variable	Description
Worked hours	Ordinal variable.
Age	Continuous variable.
Female	Dummy variable obtained from variable sex, taking value 1 if the individual is female and 0 otherwise.
Highest qualific.	Categorical variable.
Asian	Dummy variable taking value 1 if race ethnicity is Asian, and 0 otherwise.
Black	Dummy variable taking value 1 if race ethnicity is Black, and 0 otherwise.
Mixed	Dummy variable taking value 1 if race ethnicity is Mixed, and 0 otherwise.
White	Dummy variable taking value 1 if race ethnicity is White, and 0 otherwise.
Other ethnicity	Dummy variable taking value 1 if race is Other ethnicity, and 0 otherwise.
No children	Dummy variable taking value 1 if individual has no children, and 0 otherwise.
One child 0-4 age	Dummy variable taking value 1 if individual has one child aged between 0-4 years, and 0 otherwise.
One child 5-7 age	Dummy variable taking value 1 if individual has one child aged between 5-7 years, and 0 otherwise.
One child 8-9 age	Dummy variable taking value 1 if individual has one child aged between 8-9 years, and 0 otherwise.
One child 10-11 age	Dummy variable taking value 1 if individual has one child aged between 10-11 years, and 0 otherwise.
One child 12-15 age	Dummy variable taking value 1 if individual has one child aged between 12-15 years, and 0 otherwise.
One child 16-18 age	Dummy variable taking value 1 if individual has one child aged between 16-18 years, and 0 otherwise.
Two children	Dummy variable taking value 1 if individual has two children, and 0 otherwise.
$\geq$ 3 children	Dummy variable taking value 1 if individual has three or more children, and 0 otherwise.
Agriculture, mining	Dummy variable taking value 1 if individual is in the industry section agriculture or mining, and 0 otherwise.
Manufacturing	Dummy variable taking value 1 if individual is in the industry section manufacturing, and 0 otherwise.
Water, electricity	Dummy variable taking value 1 if individual is in the industry section water supply or electricity, and 0 otherwise.

Note. This Table provides a description of the variables used in the analysis. Data source is the 2021 UK Census microdata.

TABLE A.2.—
Description of variables used

Variable	Description
Construction	Dummy variable taking value 1 if individual is in the industry section construction, and 0 otherwise.
Wholesale, retail	Dummy variable taking value 1 if individual is in the industry section wholesale and retail trade, and 0 otherwise.
Transport, food	Dummy variable taking value 1 if individual is in the industry section transport or food services, and 0 otherwise.
Information, communication	Dummy variable taking value 1 if individual is in the industry section information and communication, and 0 otherwise.
Financial	Dummy variable taking value 1 if individual is in the industry section financial, insurance and real estate, and 0 otherwise.
Professional	Dummy variable taking value 1 if individual is in the industry section professional and administrative services, and 0 otherwise.
Public admin, education	Dummy variable taking value 1 if individual is in the industry section public administration and education, and 0 otherwise.
Health, social work	Dummy variable taking value 1 if individual is in the industry section human health and social work, and 0 otherwise.
Other services	Dummy variable taking value 1 if individual is in the industry section other services, and 0 otherwise.

NOTE. This Table provides a description of the variables used in the analysis. Data source is the 2021 UK Census microdata.

B Universal Credit Scheme

The Universal Credit programme is a benefit system which was introduced in 2013 as part of the statute UK Welfare Reform Act 2012.[4] The Universal Credit is responsibility of the Department of Work and Pension in Great Britain and the Department for Communities in Northern Ireland, and since 2018 all regions of the United Kingdom have been made available with the benefits of the programme.

The programme is a monthly payment made to eligible low-income individuals who are out of work, on a low hour contract or self employed contract or cannot work to support them with living costs, housing costs and childcare related costs. By 2028/2029 the Universal Credit is meant to replace all benefits related to: income support, income based Job Seeker Allowance,

[4] More details on the Welfare Reform Act 2012 are available at this link: https://www.legislation.gov.uk/ukpga/2012/5/contents.

income related Employment and Support Allowance, Housing Benefits, Working Tax Credit, Child Tax Credit. Eligible individuals encompasses individuals aged above 18 and under the state pension age, resident in the UK and not in full time education or training, among other eligibility criteria.

The Universal Credit part related to the labour market delivers benefits with the expectation that the individual worker is able to find more work if already working, or find a work in case they do not have it. Depending on the caring responsibilities, current level of earnings and health conditions of the individual, workers are placed in one of the six labour market categories depending on their efforts and ability to work, which then becomes their commitment to work more or find a job.[5]

A major boost of the benefits took place in November 2021 which reduced the taper rate from 63% to 55% constituting 8p more for every one pound received under the Universal Credit while at the same time every extra pound earned is compensated with a reduction of 55p in the benefits, and increased the work allowance by £500 annually. This boost was introduced in coincidence with the expiration in October 2021 of the £20 per week increase in the Universal Credit benefits due to the pandemic which was introduced in March 2020. According to a briefings by Brewer et al. (2021) the policy was expected to improve standard of living of 1.3 million people, however it was forecast of making worse off 3.6 million individuals because of their income fall.

The questions I investigate are: *i)* whether the Universal Credit boost of November 2021 would have been an effective policy had it been undertaken in March 2021, that is a moment of time in which low-income workers on a Universal Credit Scheme were still receiving the £20 per week allowance due to the pandemic. I examine this question on the work incentives of working hours. Then, *ii)* at age 25 low-income workers under the Universal Credit receives a substantial increase in the rate, therefore a central question is whether the age cutoff changes work incentives towards working hours. Finally, *iii)* I study the mechanism by which low-income workers change their hours of work taking into account different economic factors that can influence their decisions to work more.

C Robustness Analysis

[5] A detailed description of the categories is available under the general guidance of the Universal Credit in the House of Commons Library papers archive.

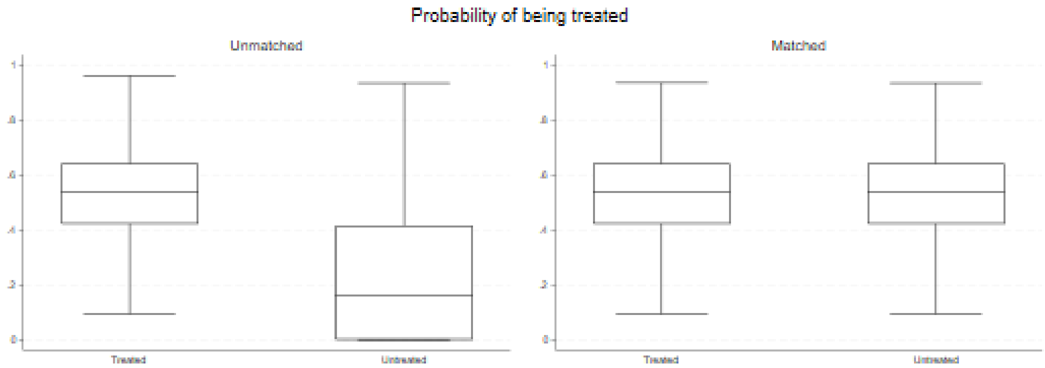

FIG. C.1.—Probability of being treated

NOTE. The figure shows the quality of the matching before and after the propensity score matching of the regressors. Data source is the 2021 UK Census microdata.

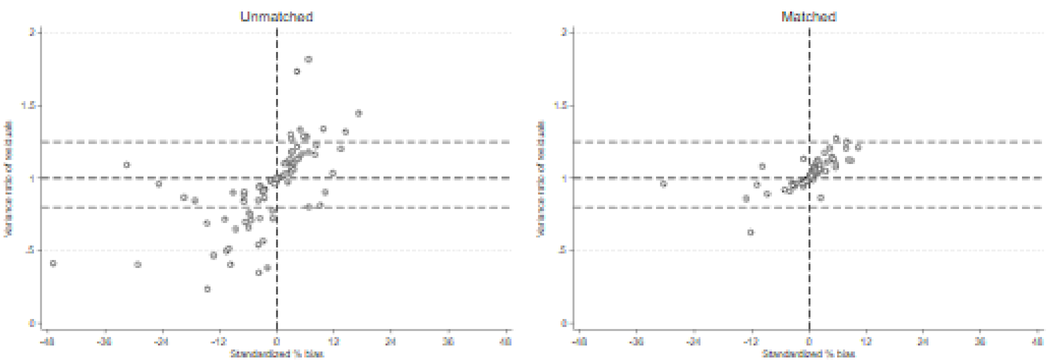

FIG. C.2.—Probability of being treated in Mahalanobis metric distance matching

NOTE. The figure shows the variance ratio for matched and unmatched sample with Mahalanobis metric matching distance of the propensity score matching estimation. Data source is the 2021 UK Census microdata.

Table A.3.—
Descriptive statistics of variables

	Female			Male		
	Mean	Obs	Percent	Mean	Obs	Percent
Worked hours	1.681	33,013	31.85	1.703	70,637	68.15
$\leq$ 15 hours		10,514	31.85		20,985	29.71
$\leq$ 30 hours		22,499	68.15		49,652	70.29
Ethnicity	3.310	33,013	31.85	3.653	70,637	68.15
Asian		6,073	18.40		4,504	6.38
Black		2,861	8.67		5,378	7.61
Mixed		990	3.00		2,179	3.08
White		20,925	63.38		56,634	80.18
Other		2,164	6.55		1,942	2.75
High qualif	2.735	33,013	31.85	3.008	70,637	68.15
No qualification		7,274	22.03		10,156	14.38
Level 1, entry level		4,501	13.63		8,714	12.34
Level 2, $\geq$ 5 GCSEs		4,332	13.12		12,361	17.50
Apprenticeship		1,970	5.97		3,070	4.35
Level 3, $\geq$ 2 A level		4,752	14.39		13,819	19.56
Level 4, degree		8,897	26.95		20,527	29.06
Other, vocation or work		1,287	3.90		1,990	2.82
Industry section	6.730	33,013	31.85	8.308	70,637	68.15
Agriculture, mining		160	0.48		242	0.34
Manufacturing		1,449	4.39		1,856	2.63
Water, electricity		225	0.68		213	0.30
Construction		3,923	11.88		1,132	1.60
Wholasale, retail		7,455	22.58		13,864	19.63
Transport, food		7,707	23.35		9,177	12.99
Information and comm		882	2.67		870	1.23
Financial, insurance		612	1.85		1,650	2.34
Professional, admin		4,112	12.49		9,435	13.36
Publib admin, education		2,339	7.09		10,099	14.30
Health and social work		1,988	6.02		17,015	24.09
Other services		2,151	6.52		5,084	7.20
Children	5.728	17,796	26.09	5.398	50,410	73.91
No children		3,887	21.84		10,746	21.32
One child, $\leq$ 4 years		623	3.50		3,100	6.15
One child, 5-7 years		484	2.72		2,107	4.18
One child, 8-9 years		532	2.99		2,106	4.18
One child, 10-11 years		1,499	8.42		4,530	8.99
One child, 12-15 years		148	0.83		1,137	2.26
One child, 16-18 years		2,322	13.05		6,959	13.80
Two children		6,123	34.41		15,269	30.29
$\geq$ Three children		2,178	12.24		4,456	8.84

Note. This Table presents mean, number of observations and proportion of variables used in the model. Data source is the 2021 UK Census microdata.

TABLE A.4.—
Descriptive statistics of variables, continuation

	Female			Male		
	Mean	Obs	Percent	Mean	Obs	Percent
Housing tenure	1.634	32,365	31.51	1.577	70,361	68.49
Social rented		11,935	36.87		29,904	42.50
Private rented		20,430	63.12		40,457	57.50
Household deprivation	1.857	32,365	31.51	1.713	70,361	68.49
No deprived		12,514	38.67		32,300	45.91
One dimension		13,271	41		27,668	39.32
Two dimensions		5,345	16.51		8,757	12.45
Three dimensions		1,154	3.57		1,528	2.17
Four dimensions		81	0.25		108	0.15
Education deprivation	0.226	32,365	31.51	0.179	70,361	68.49
Educat not deprived		25,038	77.36		57,751	82.09
Education deprived		7,327	22.64		12,600	17.91
Employment deprivation	0.091	32,360	31.50	0.069	70,358	68.50
Employm not deprived		29,404	90.87		65,499	93.09
Employment deprived		2,956	9.13		4,859	6.91
Health deprivation	0.299	32,365	31.51	0.282	70,361	68.49
Health not deprived		22,671	70.05		50,502	71.78
Health deprived		9,694	29.95		19,859	28.22
Housing deprivation	0.240	32,365	31.51	0.183	70,361	68.49
Housing not deprived		24,595	75.99		57,481	81.69
Housing deprived		7,770	24.01		12,880	18.31

NOTE. This Table presents mean, number of observations and proportion of variables used in the model. Data source is the 2021 UK Census microdata.

TABLE C.1.—

Impact of the programme boost

Variable	Treated	Control	% Bias	Bias non overlap	Variance ratio
Age					
Unmatched	38.322***	37.049***	11.8		1.03
Matched	38.322***	37.723***	5.5	52.9	1.07
Ethnicity Asian					
Unmatched	0.094***	0.141***	-14.6		0.69*
Matched	0.094*	0.088*	2.00	86.6	1.05
Ethnicity Black					
Unmatched	0.120***	0.070***	17.2		1.45*
Matched	0.120***	0.094***	8.9	48.3	1.12
Ethnicity White					
Unmatched	0.719**	0.709**	2.3		0.97
Matched	0.719***	0.769***	-10.9	-383.2	0.95
Married					
Unmatched	0.317***	0.399***	-17.2		0.84
Matched	0.317***	0.334***	-3.5	79.5	0.97
Registered partners.					
Unmatched	0.002***	0.003***	-2.9		0.57*
Matched	0.002	0.002	0.0	100.0	1.00
Level 2 qualif.					
Unmatched	0.174***	0.123***	14.4		1.32*
Matched	0.174***	0.155***	5.6	61.4	1.10
Children aged 0-4					
Unmatched	0.079***	0.112***	-10.9		0.72*
Matched	0.079	0.083	-1.2	89.4	0.96
Children aged 5-7					
Unmatched	0.040	0.041	-0.3		0.98
Matched	0.040	0.041	0.4	-65.6	1.02
Place of work, no home					
Unmatched	0.720***	0.674***	10.1		0.90
Matched	0.720***	0.765***	-9.8	3.6	1.08
Transport bus					
Unmatched	0.128	0.125	0.7		1.01
Matched	0.128	0.093	10.4	-1,472.9	1.21
Industry, manufacturing					
Unmatched	0.026***	0.038***	-6.6		0.70*
Matched	0.026	0.024	1.5	77.3	1.11
Industry, wholes. retail					
Unmatched	0.231	0.236	-1.3		0.98
Matched	0.231***	0.267***	-8.7	-574.5	0.89
Depriv. education					
Unmatched	0.246***	0.334***	-19.5		0.87
Matched	0.246***	0.305***	-13.2	32.2	0.86

NOTE. This Table presents results of the average treatment effect on treated for the Universal Credit boost with Mahalanobis metric matching distance. Variance ratio is the variance of treated over control. Significance for equality in means is ***$p< 0.01$, **$p< 0.05$ and *$p< 0.10$ critical values. **$v(< 0.5, > 2)$ and *$v[0.5, 0.8)|(1.25, 2]$ in variance ratio indicates a ratio of bad and of concern, respectively. Data source is the 2021 UK Census microdata.

TABLE C.2.—
Impact of the programme boost

Variable	Treated	Control	% Bias	Bias non overlap	Variance ratio
Depriv. housing					
Unmatched	0.299***	0.417***	-24.8		0.96
Matched	0.299***	0.315***	-3.3	86.5	0.95
Depriv. health					
Unmatched	0.405***	0.560***	-31.5		1.09
Matched	0.405***	0.555***	-30.5	3.2	0.96
Depriv. employm.					
Unmatched	0.050***	0.202***	-46.8		0.41**
Matched	0.050***	0.090***	-12.2	73.9	0.63*
Social position					
Unmatched	3.111***	3.027***	9.1		0.81
Matched	3.111	3.103	0.8	91.0	0.99
Size household, 2					
Unmatched	0.303	0.297	1.4		1.02
Matched	0.303	0.327	-5.1	-269.0	0.92
Size household, 3					
Unmatched	0.202***	0.188***	3.5		1.06
Matched	0.202	0.207	-1.3	63.8	0.97
Size household, 5					
Unmatched	0.156*	0.149*	1.9		1.03
Matched	0.156***	0.143***	3.6	-86.4	1.05
Accommodation type					
Unmatched	2.912***	2.977***	-6.0		0.66*
Matched	2.912**	2.885**	2.5	58.4	0.86
Occupation					
Unmatched	76.243***	74.631***	6.6		0.80
Matched	76.243	76.520	-1.1	82.8	1.13
Pseudo R^2					
Unmatched	0.308				
Matched	0.180				
LR χ^2					
Unmatched	$13,871$***				
Matched	$5,681.50$***				
Bias in means					
Unmatched	6.8				
Matched	2.8				
Rubin B					
Unmatched	123.1*				
Matched	87.1*				
Rubin R					
Unmatched	0.01*				
Matched	0.01*				

NOTE. This Table presents results of the average treatment effect on treated for the Universal Credit boost with Mahalanobis metric matching distance. Variance ratio is the variance of treated over control. Significance for equality in means is ***p< 0.01, **p< 0.05 and *p< 0.10 critical values. **v($< 0.5, > 2$) and *v$[0.5, 0.8)|(1.25, 2]$ in variance ratio indicates a ratio of bad and of concern, respectively. Data source is the 2021 UK Census microdata.