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Mind vs Matter: Economic and psychologic determinants of takeup rates of social benefits in the UK

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MIND VS MATTER: ECONOMIC AND PSYCHOLOGIC DETERMINANTS OF TAKE-UP RATES OF SOCIAL BENEFITS IN THE UK

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Abstract

This paper investigates the behavioural dynamics of the take-up of social benefits in the UK. Utilising data from the first nine waves (2010-2019) of the UK Household Longitudinal Study (UKHLS) and eligibility simulations based on the UKMOD tax-benefit calculator (UKHLS-UKMOD), the study finds that there is a significant state dependence effect once initial conditions and unobserved heterogeneity are considered. While economic factors are found to play an important role in explaining the take-up of social benefits, personality traits and cognitive skills do not exhibit a strong and direct influence on the take-up of social benefits. The study concludes by discussing policy implications.

1. INTRODUCTION

Not all eligible individuals for social benefits choose to claim them. The available evidence, although limited, indicates that take-up rates – defined as the percentage of eligible individuals who choose to enrol in a programme – are far from perfect. A review of the literature reveals that there exist significant variations in the take-up rates of social benefits across European states (Currie, 2004; Hernanz, Malherbet and Pellizzari, 2004; Matsaganis, Paulus and Sutherland, 2008; Bargain, Immervoll and Viitamäki, 2012; Bruckmeier and Wiemers, 2012, 2017; Dubois and Ludwinek, 2015; Harnish, 2019; Fuchs *et al.*, 2020). A recent study surveying take-up rates in 20 high-income countries found that less than one-fifth of welfare programmes had a take-up of 80% or higher, while nearly one-quarter had take-up rates of 40% or less (Ko and Moffitt, 2024). Nonetheless, the dynamics of take-up decisions remain not well understood.

Previous literature highlights various cognitive and behavioural barriers that influence decision-making. These include limited comprehension of programme rules and incentives (Duflo *et al.*, 2006; Bhargava and Manoli, 2015; Liebman and Luttmer, 2015), low awareness of the programmes themselves (Chetty and Saez, 2013; Chetty, Friedman and Saez, 2013; Barr and Turner, 2018), procrastination (Bertrand, Mullainathan and Shafir, 2006), inattention (Karlan *et al.*, 2016), psychological barriers stemming from programme complexity (Bertrand, Mullainathan and Shafir, 2006), and feelings of stigma associated with programme enrolment (Celhay, Meyer and Mittag, 2022, 2024). By considering both economic and psychological dimensions, this paper provides a comprehensive understanding of the multifaceted determinants influencing take-up rates of social benefits in the UK.

The objectives of this paper are threefold. The first objective is UK-specific and focuses on updating estimates for the UK context, where information on how take-up rates for various benefits changed over time is limited, and the existing literature is quite dated (Blundell, Fry and Walker, 1988; Craig, 1991; Pudney, Hancock and Sutherland, 2006; Hernandez and Pudney, 2007; Zantomio, Pudney and Hancock, 2010; Zantomio, 2015). The paper investigates the dynamics of individual behaviour over time, exploring why eligible individuals claim benefits and whether certain social groups are more predisposed to do so.

The second and third objectives address broader questions, where research findings for one specific country might hold a more general validity. The paper aims to explain the dynamics of take-up decisions by disentangling the effects of individual characteristics from those of state dependence, which holds significant policy implications. By distinguishing the role of heterogeneity and state dependence, policymakers can better target their intervention to increase take-up, for instance, by offering targeted help for first-time applicants.

Finally, the paper investigates the role of social networks in shaping individual take-up behaviour. Although it is difficult to measure the social network effect due to data limitations, the paper attempts to analyse its influence by analysing take-up behaviour at a fine-grained geographical detail, under the assumption that social networks fade away with distance. We cannot, however, determine whether this social network effect arises due to easier access to information, social norms, or emulation.

We construct a model of take-up decisions for two important classes of benefits in the UK. The first one is Child Benefit (CB), an allowance the government pays to help parents or guardians with the costs of raising a child. The second one is a combination of benefits that form the core of social assistance in the UK context. They comprise six different means-tested benefits (collectively referred to as Legacy Benefits, LB), that are being progressively replaced by a single monthly payment, Universal Credit (UC).[1] The two types of benefits are very different: CB has a broad target with little means testing – in effect a middle-class benefit – while LB/UC directly address situations of need, with significantly more means-testing and conditioning. It is, therefore, particularly interesting to analyse to what extent the mechanisms explaining take-up behaviour are the same, and whether any difference can be related to specific design features of the two schemes.

The dynamic aspects of take-up are captured by relating claimants' current take-up to their lagged take-up state and by allowing for correlations between observed characteristics and unobserved heterogeneity. More in detail, we employ the 'lagged

[1] The LB and UC are analysed together due to practical necessity. It is the only measure of take-up that can be measured consistently using UKMOD. It is difficult to distinguish between eligibility of LB and UC. UC is a social welfare programme in the UK that combines six different means-tested benefits (collectively referred to as LB) into a single payment. It was initially introduced as a pilot programme in 2013 and gradually expanded to replace the existing benefits system. The introduction of UC took place gradually in different phases. LB claimants had the option to migrate by voluntarily submitting a UC claim, which automatically closed their LB claim. As from 2019, the government began gradually replacing the LB system with UC, also known as "managed migration". As a result, legacy claimants who have not experienced a change in circumstances started to be approached to submit a UC claim. The main managed migration started from 2023 onwards.

dependent variable' model, used *inter alia* for the analysis of the dynamics of social assistance recipiency (Cappellari and Jenkins, 2014), and in other contexts, such as the dynamics of unionisation (Vella and Verbeek, 1998), the dynamics of low pay (Cai, Mavromaras and Sloane, 2018), and the dynamics of unemployment (Stewart, 2007). To account for initial conditions, we employ the conditional maximum likelihood estimator proposed by Wooldridge (2005).

The data used in this study are drawn from the first nine waves of the UK Household Longitudinal Study (UKHLS), adjusted to be used as input data for the UKMOD tax-benefit microsimulation model (Richiardi, Bronka and Popova, 2023).[2] UKMOD permits the simulation of eligibility for and amount of various social benefits. Using UKHLS as input data allows us to track individuals over multiple years.

The findings reveal that the level of benefits, state dependence, and factors related to demographics and socioeconomics – what we refer to as 'Matter' in the title – are important factors in determining who claims social benefits. As for 'Mind', we find that personality traits have only a weak direct relationship with take-up. Although not uncontroversial, in our narrative, we include neighbourhood effects as pertaining to 'Mind' – social norms, stigma, and emulation are clearly psychological factors that affect how material costs and benefits are evaluated, while the information channel is harder to classify. We find that the greater the take-up in the area where an individual resides compared to other areas, the more likely that individual is to claim the benefit.

The rest of the paper is organised as follows. Section 2 provides a brief literature review of the main determinants of take-up behaviour and the effects of personality traits, which serve as the conceptual basis for this study. Section 3 describes our empirical strategy, followed by the data used in the empirical analysis. Section 4 presents and discusses the main estimation results concerning the determinants of take-up of CB and LB/UC separately. Section 5 summarises the main conclusions.

2. BRIEF LITERATURE REVIEW

2.1 Factors affecting take-up behaviour

Non-take-up of social benefits affects intended targeting.[3] This, in turn, distorts the original aims of the policies and their reach. This is particularly true for means-tested benefits designed to provide essential resources to low-income households. If beneficiaries do not claim these benefits, their effectiveness in redistributing income

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[2] The standard version of UKMOD uses input data coming from the Family Resources Survey (FRS), a cross-sectional dataset.

[3] Another deviation from designed targeting involves overpayments to individuals who are not eligible but still claim the benefit. While this may be exacerbated by behavioural traits affecting knowledge of and compliance with the rules, it remains mostly an administrative problem in controlling eligibility. This issue is likely to be relatively minor in systems with a more advanced administrative capacity (such as the UK). Non-take-up can also have an administrative component – for instance, when applications are lost or processed with delays or when the administrative hurdle for claiming is too high – but behavioural aspects are more likely to play a major role.

and reducing poverty can be seriously compromised (Matsaganis, Paulus and Sutherland, 2008).

Imperfect take-up of welfare payments also has budgetary implications. While an imperfect take-up may result in lower-than-expected budgeted outlays in the short term, it can exacerbate government spending over the long term. This is because non-take-up may lead to poorer nutrition, delayed medical care, and an impoverished environment, to name a few. Hence, policymakers need to ensure that eligible individuals are aware of the benefits and encouraged to claim them so that welfare schemes can provide essential resources to those in need and act as automatic stabilisers during difficult times.

Several factors, including both recipient characteristics and administrative procedures, are known to influence the occurrence of non-take-up, shaped by welfare policy design and the broader social and legal context (van Oorschot, 1996, 2002; Janssens and Van Mechelen, 2022). Economists have traditionally ground their understanding of benefit take-up on the rational choice theory (Moffitt, 1983; Duclos, 1995; Atkinson, 1996; Hernandez and Pudney, 2007), which sees the claiming process as a utility-maximising decision under uncertainty. According to this framework, individuals weigh the trade-off between anticipated benefits and the costs of accessing social benefits, including psychological costs. Indeed, Moffitt (1983) identifies stigma as the main cost of participation in a means-tested programme, though his model has been extended to include other cost types.

There are four main categories of barriers that can impact take-up rates (Craig, 1991; van Oorschot, 1996; Hernanz, Malherbet and Pellizzari, 2004). These include (i) expected level and duration of entitlement to benefit, subject to uncertainty about the outcome of the application (Creedy, 2002; Dahan and Nisan, 2010); (ii) information costs, i.e., the time and effort required for understanding entitlement rules and mastering application procedures (Van Parys and Struyven, 2013); (iii) transaction costs associated with gathering proof of eligibility, administrative delays and errors; and (iv) psychological costs, including stigma associated with applying for benefits. If the stigma associated with claiming the benefit is high, individuals may fear disapproval from others or perceive it as a personal shortcoming for needing assistance rather than being able to support themselves. In the case of the latter, stigma becomes internalised, leading to personal costs such as low self-esteem rather than social costs (Elster, 1989, p. 119).

Indeed, recent work by Celhay et al. (2022) and Celhay et al. (2024) investigating the association between underreporting of welfare participation and true local welfare participation revealed a negative relationship, implying the existence of stigma costs associated with claiming benefits. Also, individuals generally more associated with labour market participation, such as higher educated and younger persons, may suffer from (perceived) stigma effects and work the hardest to avoid transfer dependence (Bruckmeier and Wiemers, 2012, 2017; Bruckmeier, Müller and Riphahn, 2014). All these factors interact with each other and are also influenced by the administrative, institutional, and broader social context, which can create additional barriers to applying for benefits.

There are two additional factors to consider in this basic model. The first factor is the role of social networks in reducing the cost of making a claim (Currie, 2004; Celhay, Meyer and Mittag, 2024). Social networking can affect take-up behaviour through an information channel and through normative preferences. The information channel refers to how the behaviour of others can shape what individuals know, and what they think they know. For example, community-based knowledge-sharing can reduce information-related costs by providing information on how to deal with administrative requirements or maximise expected benefits. Interactions with benefit recipients can also create a perception that benefits are easily accessible – 'the availability heuristic' (Tversky and Kahneman, 1982). Imitating the behaviour of acquaintances can also be partly attributed to the information channel, as when the cost of acquiring and processing information is high, copying others might be a good strategy.

On the other hand, normative preferences explain how individuals might wish to conform to others – and to views held by others – either because they gain utility from adopting a social norm or because they want to avoid disutility from not adopting it (stigma). This effect might help explain why take-up rates vary between different social networks: where a culture of independence and self-reliance prevails, people might decide not to claim welfare benefits they are entitled to, despite their needs; on the other hand, a lower stigma from welfare participation might push up take-up rates where a culture of dependency prevails (Bertrand, Luttmer and Mullainathan, 2000; Stuber and Schlesinger, 2006; Baumberg *et al.*, 2012; Holford, 2015).[4]

Recent research by Celhay et al. (2022) indicates that stigma decreases with local participation, suggesting that peer evaluation shapes concerns about social image and may give rise to what economists term "positional externalities" (Bursztyn *et al.*, 2018). In a similar vein, Baumberg et al. (2012) also report that individuals in social housing perceive that society at large might not judge them as harshly for claiming benefits, however, they feel similar self-stigma for claiming benefits. This suggests that while the perceived negative consequences of engaging in socially undesirable behaviour decrease as more peers engage in the same behaviour, personal feelings (self-stigma) persist even when the take-up of benefits is not observed or exposed to society at large.

The second factor identified by Currie (2004) takes the form of time-inconsistent preferences. This happens because the costs of claiming are borne immediately, while the benefits are uncertain and will be received at a later time. As a result, some

[4] For normative preferences, it is not only the number of people in the social network who are claiming the benefits that matter, but also the importance of those other claimants to the individual. For example, the reference group theory suggests that a person is more likely to follow other claimants and claim the benefit themselves, the more important those who receive the benefit are as reference persons for the individual (Merton, 1968).

individuals may choose not to claim the benefits, even though they would have benefited from doing so in the future.

2.2 Personality, information costs and stigmatisation

Personality traits are "relatively enduring patterns of thoughts, feelings, and behaviours that differentiate individuals from one another" (Roberts, 2009, p. 2). They, therefore, represent general cognitive, affective, and behavioural patterns, i.e., what the individual is likely to do averaged over situations. The Big Five model comprises five broad domains of personality traits, including openness to experience (creativity, curiosity, honesty/humility, and inquisitiveness), conscientiousness (self-discipline, punctuality, competence, and organisation), extraversion (talkativeness, friendliness, energy, and outgoingness), agreeableness (kindness, generosity, warmth, and charity), and neuroticism (fear, worry, stress, and paranoia).[5] Each trait is not the sole determinant of behaviour but a contributing factor in a given context. Therefore, the Big Five model helps us understand fundamental mechanisms driving human behaviour.

Research linking the Big Five traits to welfare recipients has been scarce to date. However, a recent study using vignette-based experiments sheds some light on how welfare recipients are perceived. Schofield et al. (2019) found that individuals receiving unemployment benefits were perceived as less conscientious, more extroverted, and less agreeable compared to those not receiving benefits. No notable differences in openness to experience and emotional stability were found.

Personality traits can help explain why some people do not claim social benefits. Studies have shown that individuals who are open to new experiences and exhibit agreeable traits tend to face less public stigma and prejudice (Ekehammar and Akrami, 2003, 2007; Yuan *et al.*, 2018; Solmi *et al.*, 2020; Weinberg and Soffer, 2023). Conversely, people who have low levels of openness often conform to societal norms and may hold specific prejudices, such as anti-immigrant or racist attitudes (Sibley & Duckitt, 2008). Additionally, research has shown that those with high openness scores are more inquisitive and driven to enhance their abilities and knowledge (Komarraju and Karau, 2005; Komarraju, Karau and Schmeck, 2009; Clark and Schroth, 2010). This implies that those with higher openness may be more inclined to participate in welfare programmes due to the lower transaction costs associated with acquiring and processing information.

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[5] The five factors are believed to be broad and capture the fundamental and general aspects of thought, feeling, and behaviour that people typically do differently (McCrae & John, 1992) (John, et al., 2010). The five-factor model has also taken a prominent place in economic research and is considered a standard module in most longitudinal data sets (Vella, 2024). Although the five-factor model is not without criticism (Block, 2010; Eysenck, 1992), it has been extensively linked to life outcomes, such as wages, health, and longevity (Heckman, et al., 2021). The five-factor model has long been recognised as internally consistent, stable, and enjoys cross-cultural support (John, 2011).

Turning to conscientiousness, research has consistently shown that individuals with this trait tend to be motivated, self-sufficient, and organised (Egan *et al.*, 2017). As a result, they are more likely to set and achieve ambitious goals and to approach tasks diligently. When it comes to benefits take-up, conscientious individuals may be more inclined to utilise contributory benefits due to a lower perceived stigma of laziness (Brown-Iannuzzi *et al.*, 2021). However, it is also essential to consider the negative "stigma effect", as individuals with high levels of conscientiousness attach more stigma to claiming benefits (Schofield, Haslam and Butterworth, 2019). The stigma may stem from perceptions of welfare recipients as less conscientious or lazy (McKay, 2014; Schofield and Butterworth, 2015; Schofield, Haslam and Butterworth, 2019), undeserving (Jensen and Petersen, 2017; Buss, 2019), or ill-intentioned and incompetent (Fiske, 2018).

Regarding neuroticism, extant literature indicates that individuals with high levels of this trait tend to exhibit increased rates of absenteeism and decreased productivity (Egan, Daly and Delaney, 2015; Cubel *et al.*, 2016), potentially resulting in self-stigmatisation and reduced take-up.

The influence of extraversion on take-up behaviour is *a priori* less clear, as it can have both positive and negative effects. On the one hand, extroverts may benefit from lower information and processing costs because of their extensive social networks. On the other hand, extraverts may feel stigmatised if their benefit usage is seen as excessive or inappropriate. The literature about extraversion presents a blend of results. While some studies, such as Ekehammar and Akrami (2007), find a negative link to general prejudice, others, like Solmi et al. (2020) and Yuan et al. (2018), suggest a positive association with stigma. However, it is important to note that these correlations, albeit present, tend to be modest.

2.3 The role of policy and institutions

While much attention has been devoted to factors at the individual level, policy design plays a role in determining take-up behaviour. It has been argued that targeted welfare programmes aimed at specific groups often exhibit higher rates of non-take-up compared to universal programmes (Mood, 2006; Bruckmeier and Wiemers, 2012). Eligible individuals may opt not to claim targeted benefits because doing so can intensify stigma by directly confirming their need for support. This effect is more pronounced in communities that value self-dependence and personal responsibility, where individuals may fear social stigmatisation for seeking social benefits. Moreover, fragmented targeted benefits can increase information and processing costs for potential claimants. An excess of social programmes may not only increase information costs but also give rise to choice overload (Beshears *et al.*, 2013; Briere, Poterba and Szafarz, 2021).

Some contend that offering a single universal benefit (such as UC in the UK) instead of multiple targeted welfare programmes could reduce stigmatisation. A single benefit might be more visible, potentially leading to greater identification as welfare-dependent

(Kildal and Kuhnle, 2005; Larsen, 2006; Baumberg *et al.*, 2012). However, there is generally a lack of evidence to support this claim, and in the UK it has even been suggested that Universal Credit could help reduce the stigma attached to welfare payments among non-workers (Rotik and Perry, 2011).

Social stigma may persist even with universal welfare benefits (Jones, 1980; Wong, 1998). This suggests that simply reducing selective social benefits may not address the root causes of stigma. Universal benefits might also lead to a higher non-take-up rate among those who perceive it as an undeserved and unreciprocated gift rather than an entitled benefit. Entitlements are generally considered less stigmatising than non-contributory benefits. Recipients of non-contributory benefits often feel judged or looked down upon, contributing to the stigma associated with these benefits.[6]

The effect size of stigmatisation can differ depending on whether the social benefit is designed to be contributory or non-contributory. Benefits can be based on the principle of equity, where recipients are identified through contribution records, typically involving social security contributions, and the principle of support, where recipients can claim the benefit not based on insurance (non-contributory benefits). Recipients of non-contributory benefits often feel more subjected to judgment or condescension, contributing to the stigma associated with these benefits (Baumberg *et al.*, 2012).[7]

Government administrations also play a role in affecting take-up rates. To enhance take-up, administrations have adopted strategies from large-scale digitalisation efforts to establishing one-stop shops. This approach allows individuals applying for one benefit to receive automatic information about other programmes they may be eligible for. Moreover, administrators can proactively identify eligible claimants or implement an automated registration process, such as accessing the registry of registered unemployed individuals. Clear and effective communication campaigns have also been shown to boost the uptake of benefits (Bhargava and Manoli, 2015; Gestel *et al.*, 2023).

3. ANALYTICAL STRATEGY

3.1 Measuring take-up

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[6] Rotik and Perry (2011) argue that some working people opposed the idea of UC because they feel they are being treated the same way as those who are out of work.

[7] A telephone survey conducted by HM Revenue and Customs in the UK in 2011 found that people who received tax credits and CB expressed more discomfort when claiming social security benefits (Breese, 2011). This was because they attributed a higher degree of stigma to the latter. According to the survey results, 25% of the respondents considered tax credits as stigmatised, while 66% associated stigma with social security benefits. Tax credits were perceived as recognition of past work contributions, so they had a reduced stigma. CB, on the other hand, had the lowest stigma likely due to its broader eligibility criteria. When respondents were asked about the household income limits for CB eligibility, a notable distinction emerged at higher income levels, where there was greater support for providing CB as compared to Tax Credits. This distinction could be attributed to the universal nature of CB during the survey period.

One of the main challenges in studying the take-up of social benefits through empirical analysis lies in accurately measuring it. A precise measure of take-up rates necessitates valid information on both programme eligibility and recipients. However, this can prove to be a difficult task, primarily because the eligible population is not directly observable in survey data (nor it is generally known in administrative sources). Moreover, household eligibility may change between the time the household sought entry to the welfare programme and when it was surveyed. Duclos (1995) further elaborates on this using econometric methods to show that analyst error can lead to substantial misestimates of take-up rates.

Given that eligibility is generally not observable, one has to resort to simulating benefit entitlements, where policy rules, including eligibility criteria and means-testing thresholds, are implemented on an observed population of interest.

Take-up rate is then measured as

$$\text{take-up} = \frac{\text{observed recipiency}}{\text{simulated eligibility}} \tag{1}$$

If using administrative data on recipients, we can assume that measurement error on the numerator is not an issue, while approximations in the simulation of eligibility criteria and measurement errors in the characteristics of the population used for simulating eligibility potentially bias the denominator. Administrative data on actual recipients is not publicly available, at least in the UK. Instead, we recur to survey data, exploiting available information on detailed income sources. Several factors, however, can contribute to the mismeasurement of benefit receipt in survey data. For example, some respondents may have forgotten about past benefit receipt (recall bias) or may have reported past benefit receipt as more recent than it occurred (Celhay, Meyer and Mittag, 2024). Additionally, respondents who claim multiple benefits may misreport by inadvertently omitting received benefits and reporting unreceived ones (Hancock and Barker, 2005; Call *et al.*, 2013; Krafft, Davis and Tout, 2015), a phenomenon referred to as benefit confusion. Another contributing factor to misreporting is the “social desirability bias” (Bound, Brown and Mathiowetz, 2001; Celhay, Meyer and Mittag, 2024), which occurs when the receipt of means-tested social welfare benefits is perceived as stigmatising, leading respondents to underreport their receipt of these benefits. For instance, individuals who are close to the labour market, without children, and with relatively high household incomes and savings are likely to under-report their welfare receipt (Bruckmeier, Müller and Riphahn, 2014).

Some studies discussed the relevance of misreporting for the reliability of survey data. Meyer et al. (2022) found that between 23% and 50% of actual food stamp recipient households in the USA do not report benefit receipts, and a substantial number of actual nonrecipients are also recorded as recipients. The study also found that error rates vary with household characteristics. Similarly, Bruckmeier et al. (2021) investigated the take-up for the German minimum income support programme Unemployment Benefit II (UB II) and found instances of both under- and overreporting of benefit programme participation in survey data when compared to linked administrative records. Their analysis of corrected versus uncorrected data showed statistically significant and substantial differences in estimated marginal effects, suggesting that correcting for misreporting not only alters the magnitude of non-take-up but also modifies the influence of factors associated with the decision to avail benefits. Additionally, Krafft et al. (2015), utilising pooled data across two states in the USA, explored factors influencing subsidy using both survey and administrative datasets. The study found that the frequency and systematic nature of misreporting bias estimates of the predictors of programme receipt.

Measuring take-up is subject to various sources of measurement errors, both at the numerator and at the denominator of eq. (1) (see Table 1). To start with the numerator (observed behaviour), individuals might not report receiving the benefit, for instance, for recall errors or to avoid feeling stigmatised (false negatives). If eligibility is correctly simulated, they would be wrongly classified as non-take-uppers.[8] Conversely, false positives can occur if individuals incorrectly report receiving the benefit, for instance, because they confuse the month when they claimed it. If they are simulated as eligible, this would result in an upward bias in the take-up rates.[9]

False positives and false negatives can also occur at the denominator, determining (simulated) eligibility. Over- (under-) estimation of eligibility would then result in a downward (upward) bias in the take-up rates.

Table 1. Measurement errors

Affecting the numerator		
	Observed recipiency	
True recipiency	Yes	No
Yes		Take-up biased downwards
No	take-up biased upwards	

Affecting the denominator		
	Simulated eligibility	
True eligibility	Yes	No
Yes		take-up biased upwards
No	take-up biased downwards	

Measurement errors in a binary dependent variable can lead to biased coefficient estimates, even if the measurement error is independent of covariates, as opposed to a continuous variable (Hausman, Abrevaya and Scott-Morton, 1998; Bound, Brown and Mathiowetz, 2001). If take-up is measured with random error, the coefficient

[8] If, on the other hand, they are (incorrectly) simulated as non-eligible, they would be dropped from the analysis, still resulting in a downward bias in the estimated take-up rate, although less severe.
[9] From the data, we observe that the false positive error rate is 6.8% for CB and 10.4% for LB/UC. The false negative is unmeasurable.

estimates for predictors of take-up will be biased towards zero.[10] If, on the other hand, the measurement error is systematically related to the covariates, the estimated coefficients in a model with take-up as the dependent variable can be biased in either direction.

However, we do not expect measurement error in take-up rates to be unduly high, because of the high-quality of both the survey data (Fisher and Hussein, 2023), and the tax-benefit model (van de Ven and Popova, 2024), which has undergone extensive validation. Furthermore, given that the focus of the study is on analysing *changes* in take-up rates over time, the problem would be, to a considerable extent, differenced out. Nevertheless, we subject results to a robustness test where we extend the pool of eligible individuals to include cases who are not simulated to be eligible, but are observed to receive the benefits. If selective measurement error were an issue, including these individuals in the analysis would lead to significant changes in the results.

3.2 Microsimulation and data

To simulate benefit entitlements, we use UKMOD, which is based on the UK component of EUROMOD (Sutherland and Figari, 2012). UKMOD is a static microsimulation model comprising a detailed implementation of the UK tax and transfer system (Richiardi, Collado and Popova, 2021). The model is mainly used for the ex-ante evaluation of social policy reforms directed at households in the UK. The model has been validated and tested at the micro and macro levels (van de Ven and Popova, 2023).

The standard version of UKMOD is based on FRS data. The cross-sectional nature of the data, however, precludes analysis of persistence in take-up behaviour. Therefore, this study uses a version of UKMOD that utilises longitudinal data from UKHLS, recently made available for research (Richiardi, Bronka and Popova, 2023).

UKHLS is an ongoing panel survey of over 40,000 households that started in 2009 (Univeristy of Essex, 2019). Study design involves oversampling of certain segments of the UK population, including regions such as Northern Ireland, as well as areas within England, Scotland, and Wales with significant migrant and ethnic minority populations. Further details regarding the sampling frame and data collection procedures can be found in (Burton, Laurie and Lynn, 2011).

For this research, we have used the first nine waves of UKHLS, which allow us to measure how individual eligibility and benefit recipiency change over time for a large sample of benefit units. Another advantage of using UKHLS data comes from the fact that the survey includes information on various life course domains. This permits a

[10] When a continuous variable is mismeasured, it is possible to use instrumental variable techniques to correct for random measurement errors. However, when it comes to binary variables, instrumental variable techniques cannot be used because measurement errors in binary variables are mean-reverting and are correlated with the true value (Bound, Brown and Mathiowetz, 2001).

comprehensive understanding of the factors that influence the take-up rates of social benefits in the UK.

While the UKHLS data used in this study is not specifically meant to measure income, it nevertheless provides high-quality income data (Fisher and Hussein, 2023). The survey aims to collect data on household incomes after taxes and National Insurance contributions. To do this, each individual in the household is asked about each income source they have. A comprehensive set of income sources is collected, up to 46 in total, including earnings from jobs, social security benefits, pensions, and investment income. Total household income is then computed by summing over individual income sources, for all household members.

There are several other aspects of the survey that increase the reliability of income data and reduce measurement error in take-up rates. Respondents are asked about their “current income” or income during the survey interview, which allows validation with official UK (cross-sectional) income statistics. For specific income sources, respondents are allowed to choose the reporting period, and the reported amounts are standardised post-data collection. Deriving final household net income involves data cleaning to identify reporting errors where they are clear, imputation for missing data, and simulation for tax calculations. If a household reports the same income source more than once (for example, if both members of a couple report receiving the same state benefit), this is identified to avoid double-counting. Additionally, deductions for household taxes are made using external information on council tax. This implies that the potential measurement error in reported incomes is likely to be low.[11] Nevertheless, as a robustness test, we include individuals in the eligible population who are simulated not to be eligible but still receive benefits. The presence of non-random measurement error will potentially lead to significant changes in the reported results.

Finally, by linking the UKMOD-UKHLS input data with the special license version of UKHLS, we can attempt a geographical characterisation of take-up rates across the UK. This linkage allows us to calculate the take-up in each local authority district. To address the potential problem of endogeneity between take-up rate and the proportion of recipients in each local area district, we recalibrate the ratio by excluding the eligibility unit from the count of eligible units of the benefit and those claiming the benefit if the unit is already claiming the benefit.

3.3 Measuring personality traits and cognitive skills

The third wave of the UKHLS includes a module designed to construct a psychological profile of the respondent. Questions asked pertain to the Five Factor Model, which includes the fundamental psychological dimensions: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Given the impracticality of conducting extensive psychological assessments in large-scale

[11] See Fisher (2019) for further details.

surveys, the UKHLS offers a set of fifteen items, with three items dedicated to each personality dimension.[12] Respondents provide their answers using a Likert-type scale with seven points, ranging from 1 – “does not apply” to 7 – “applies perfectly” (refer to Appendix A for the list of items used). The analysis in this study utilises measures derived by standardising the scores obtained from the factor analysis. Three items were used to assess each of the five dimensions. The Cronbach's alpha was 0.57 for Agreeableness, 0.55 for Conscientiousness, 0.60 for Extraversion, 0.71 for Neuroticism, and 0.66 for Openness to Experience.[13]

In the third wave, a battery of four tests was administered to survey participants to assess cognitive ability. These tests comprise: Immediate Word Recall (quantified by the number of correct items); Subtract (assessed by the number of correct answers); Verbal fluency (evaluated by the count of correct answers) and Numeric Ability (determined by the count of correctly answered items). For this study, we obtain one standardised score from these measures, by means of a principal component analysis.

4. DESCRIPTIVE STATISTICS

This paper studies take-up rates for several benefit schemes, the first being Child Benefit (CB). CB is a universal flat-rate non-contributory benefit paid to the carer of each dependent child (under 16 or under 19 and in full-time education or training). There is a higher rate for the eldest or only dependent child; otherwise, the rate does not vary. CB is not generally taxable, and has been subject to a means-test since 2013. This involves a High Income Child Benefit Charge (HICBC), payable if the carer or their partner has an income over £50,000 in a given tax year. The amount of the tax is 1% of the benefit for every £100 of income additional to £50,000, effectively resulting in a taper rate that brings the benefit to 0 if the income of one of the two partners surpasses £60,000. These income thresholds and the HICBC have remained unchanged between 2013 and 2023.[14]

Next, we turn to Legacy Benefits (LB), a group of six different means-tested benefits in the process of being phased out: Income-based job seekers allowance, Income-Related Employment and Support Allowance, Income Support, Housing Benefit, Child Tax Credit, and Working Tax Credit. All LBs are subject to a means test and non-contributory benefits.

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[12] The full inventory, the NEO PI-R, comprises 240 questions (Costa Jr. and McCrae, 2008).
[13] The alpha value provides a measure of internal consistency, that is, how closely related a set of items are as a group. Cronbach (1951) alpha values of 0.7 or higher indicate acceptable internal consistency. Values of alpha less than 0.7 are common for one-dimensional scales with less than ten items (Cortina, 1993; Sijtsma, 2009). Although a high value of Cronbach’s alpha is desirable, there is no general rule where alpha becomes acceptable (Schmitt, 1996).
[14] The HICBC was introduced in 2013 following initial proposals announced in 2010 for withdrawing CB from families with a higher rate taxpayer, which was then modified in the 2012 Budget. Thresholds and rates were changed in the 2024 Spring budget announcement, with effects from April 6, 2024, which is beyond our period of observation.

In 2013, the UK government introduced a new social welfare programme called Universal Credit (UC), consisting in a benefit for working-age people on a low income who are in or out of work. The scheme represents a major restructuring of the UK social assistance system and has been rolled out progressively with the aim to completely replace LBs by 2028/9. It was initially introduced as a pilot programme in certain areas and later expanded across the UK. To be eligible for UC, a claimant must meet two sets of conditions: 'basic conditions' and 'financial conditions'. The basic conditions require the claimant to be over 18, under State Pension age, and not in education. The financial conditions require the benefit unit to have sufficiently low income and capital. Only one claim for UC can be made per benefit unit. Unfortunately, within the current UKMOD modelling, take-up rates cannot be analysed separately for LB and UC. Therefore, the two benefits are analysed together.

Official statistics on take-up for CB are provided by HM Revenue and Customs. Estimates reveal that the take-up rate has declined steadily over time, from 97% in 2012 to 89% in 2022. This is attributed to the introduction of HICBC in 2013, dissuading some families from claiming (HM Revenue & Customs, 2023). Additionally, the Covid-19 pandemic has likely exacerbated this decline in more recent years. The CB take-up rate is calculated using three separate data sources: (i) administrative data which is used to calculate the caseload and (ii) population data produced by the Office for National Statistics (ONS). Take-up rates are estimated by dividing administrative data totals by population figures. The Labour Force Survey (LFS) data is used to adjust rates for participation in education for 17 to 19-year-olds.

Official take-up estimates for LB and UC are not currently provided. In 2010 the take-up rate for Child Tax Credit was 83%, while the take-up rate for Working Tax Credit was 64%. From 2010 to 2012 there was a noticeable increase in the take-up rates for both credits. In 2012, the take-up rate for the Child Tax Credit peaked at 88%, while the Working Tax Credit reached a take-up rate of 66%. Subsequently, from 2013 to 2017, there were slight fluctuations in the take-up rates for both credits, with some years showing small increases or decreases (HM Revenue & Customs, 2019). The estimates published by the Department for Work and Pensions (DWP) indicate that the Housing Benefit take-up rate varied from 78% in 2016 to 83% in 2018, while the take-up rate for Income Support/ESA (Income-related) ranged from 82% in 2010 to 90% in 2019 (DWP, 2020). However, year-on-year comparisons need to be carried out with caution due to the rollout of Universal Credit (UC) and methodological refinements.

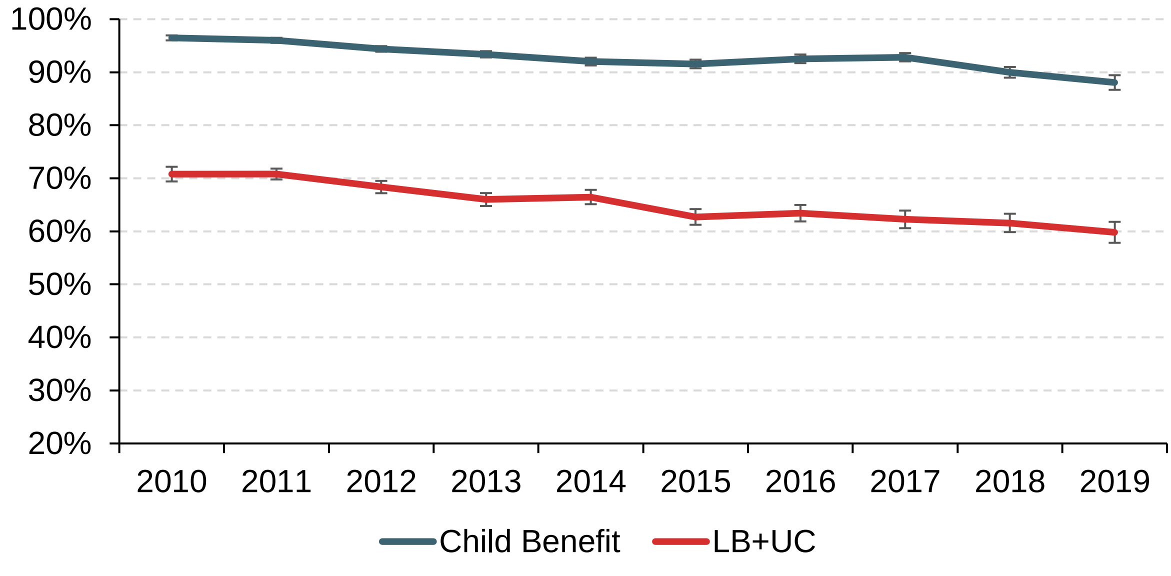
Our estimates show a marked decline for both CB and LB/UC over the years (Figure 1). Starting with CB we note that prior to the implementation of HICBC, the CB take-up remained consistently high, averaging at 96%. However, following the introduction of HICBC in 2013, there was a notable decline in overall take-up, which stood at 92% by 2015. Subsequently, the take-up rate remained relatively stable until a further decline to 88% by 2019.

One of the primary factors implicated in this decline is the introduction of the HICBC. The introduction of the HICBC has raised concerns regarding the number of taxpayers facing penalties for failing to register their HICBC liability and pay the charge through their tax return. Additionally, the lack of adjustments to the £50,000 threshold since its inception has led to more taxpayers being liable to pay the charge. Therefore, some individuals eligible for CB may opt not to claim the benefit to avoid paying the HICBC (Seely and Kennedy, 2023).

Indeed, when examining the take-up rates separately among parents with taxable income less than £50,000 per year and those with taxable income exceeding £50,000 per year, we observe a significant impact of the HICBC. While the overall decline in CB take-up rates mirrored the general trend, parents affected by the HICBC policy experienced a more pronounced decline. Specifically, their take-up declined from 92% to 63% by 2013, further dropping to 50% in 2015, before partially recovering to 59% thereafter. However, this increase needs to be interpreted with caution due to the wide confidence intervals. The study will only focus on parents below the HICBC threshold.

Likewise, LB/UC have experienced a parallel decline in its take-up rate over time, despite the gradual introduction of UC in 2013. Estimations indicate a slight recovery in 2014, but take-up has steadily declined in subsequent years. A recent report by Ipsos, commissioned by DWP, identifies various reasons for this lower take-up (NAO, 2024). These include individuals mistakenly believing that the migration notice does not pertain to them, assuming they are ineligible due to recent changes in circumstances, or having misconceptions about automatic transfer to UC.

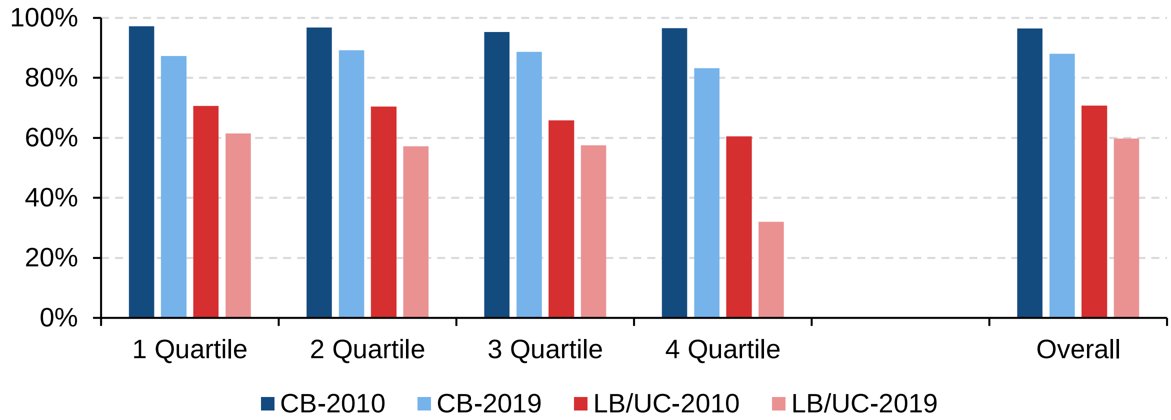
Figure 1. Take-up rates (%), 95% CI



The error bars represent the 95% confidence interval bars.
Source: our computation on UKMOD-UKHLS output data, 2010-2019

Between 2010 and 2019, take-up rates changed across different gross income levels, as shown in Figure 2, categorised by income quartiles.[15] In 2010, take-up rates for CB were consistently high, ranging from 95% to 97% across all quartiles, reflecting widespread claiming prior to HICBC. However, by 2019 there was a notable decrease in take-up, particularly evident amongst the high-income group, where the rate dropped to 83%. While the first and second quartiles experienced relatively smaller declines, they also saw decreases, indicating a general trend of reduced take-up rates over the decade. On the other hand, LB/UC in 2010 had lower take-up rates compared to CB, ranging across all income quartiles. In 2019, all income groups saw a decrease in take-up, with the fourth quartile experiencing the most significant drop to 32%. These statistics indicate that the transition to UC did not help to reverse or reduce the declining trend in take-up.

Figure 2. Take-up rates (%), by (gross) income quartile

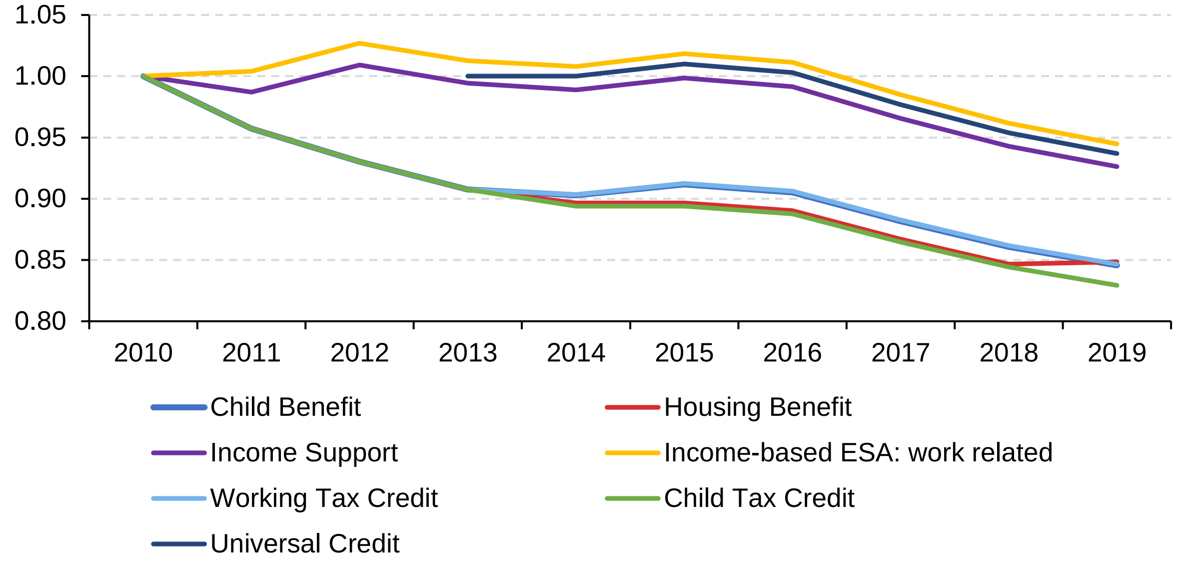


Source: our computation on UKMOD-UKHLS output data, 2010-2019

A likely explanation of the declining trends illustrated above points to the relevance of economic factors. Figure 3 illustrates the benefit rates in real terms from 2010 to 2019, presenting each benefit rate relative to its 2010 (base year) value. By 2019, the indices had decreased, indicating a reduction in each benefit's relative level of support. In real terms, all benefits were approximately 15% lower in 2019 than in 2010, except for Income Support and Income-based Employment and Support Allowance which have experienced a 6% decrease since 2010. Moreover, UC rates are also 6% lower in real terms relative to 2013. This reduction in benefit value stems from inadequate indexing of benefit amounts and may have deterred eligible individuals from taking social benefits.

[15] Gross (original) income is the sum of employment income, investment income, income of children under 16, property income, private pension, private transfers received, income from self-employment, minus maintenance payments paid.

Figure 3. Index of benefit rates, 2010 = 1.00



Source: our computation on benefit rates data, 2010-2019

Table 2 describes transitions between take-up status over the period under analysis. The data shows that there is a high level of stability, with 97% of eligible units continuing to be observed to claim the benefit the following year, while the remaining 3% is observed to stop claiming. 70% of eligible units classified as non-take-up in any year remain so in the next year, but 30% switch to (observed) take-up. A similar pattern is observed for LB/UC. Approximately 93% of eligible units who claimed the benefit in a particular year continued to claim the next year, while 80% of those who did not claim persisted in not claiming it. Moreover, there was a 30% chance that those who did not claim the benefit in a year would start claiming it the following year.

Table 2. Take-up transition matrix

	t+1		
	Child Benefit		
t	Not take-up	Take-up	Total
Non take-up	70.0%	30.0%	100%
Take-up	2.7%	97.3%	100%
Total	6.0%	93.9%	100%
	Legacy Benefits/Universal Credit		
	Not take-up	Take-up	Total
Non take-up	81.0%	19.1%	100%
Take-up	7.2%	92.8%	100%
Total	22.6%	77.4%	100%

Sample: Individuals eligible in both t and t+1.
Source: our computation on UKMOD-UKHLS output data, 2010-2019

5. MODEL SPECIFICATION

To investigate the dynamics of take-up behaviour, accounting for past behaviour and unobserved heterogeneity, we employ a dynamic random effects probit framework (Wooldridge, 2005). The inclusion of the lagged dependent variable introduces the issue of initial conditions, implicitly assuming that the initial observations are independent of unobserved variables. Simply put, this assumption implies that the behavioural process begins at the same time as the observation period for each individual. However, this assumption is too restrictive for this study, which uses data from 2010 to 2019 since, for some individuals, 2010 does not mark the start of their behavioural process. The adopted framework accounts for correlated random effects and endogenous initial conditions, allowing us to separate the contribution of genuine state dependence from various forms of (observed and unobserved) heterogeneity on take-up behaviour. The latent variable equation for the dynamic random effects panel probit model can be written as:

$$y_{it}^{*} = \mathbf{z}_i \alpha + \mathbf{x}_{it} \beta + \gamma y_{it-1} + u_i + \varepsilon_{it} \tag{2}$$

where the subscript $i = 1, 2, \dots, N$ indexes eligible units, the subscript $t = 2, \dots, T$ indexes time periods, T_{it}^{*} is the latent dependent variable for taking up the benefit, $\mathbf{z}_i$ is a vector of time-invariant characteristics, $\mathbf{x}_{it}$ is a vector of time-varying characteristics, u_i are unobserved time-invariant individual-specific random effects, and the ε_{it} are the idiosyncratic error term, and they are assumed to be normally distributed $N(0, \sigma_\varepsilon^2)$.

The observed binary outcome is:

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^{*} \geq 0 \\ 0 & \text{if } y_{it}^{*} < 0 \end{cases}$$

When unobserved individual heterogeneity influences take-up behaviour, the assumption that u_i is independent of $\mathbf{x}_{it}$ becomes invalid. To address this, we can approximate the individual effect as a function of the individual means of time-varying characteristics, following the approach proposed by Mundlak (1978):

$$u_i = \mu + \bar{\mathbf{x}}_i \boldsymbol{\delta} + \eta_i \tag{3}$$

where $\eta_i | \bar{\mathbf{x}}_i \sim N\left(0, \sigma_\eta^2\right)$ and is independent of $\mathbf{x}_{\boldsymbol{it}}$ and ε_{it}. η_i represents the residual and is assumed to be normally distributed with zero mean and variance σ_η^2, indicating the degree of dispersion due to unobserved heterogeneity.

The latent regression becomes:

$$y_{it}^{*} = \mu + \mathbf{z}_i \alpha + \mathbf{x}_{it} \beta + \gamma y_{it-1} + \bar{\mathbf{x}}_i \boldsymbol{\delta} + \eta_i + \varepsilon_{it} \tag{4}$$

A test of $\operatorname{cov}(\eta_i, \mathbf{x}_{it}) = 0$ is a test of $H_0\colon \boldsymbol{\delta} = 0$. If the test rejects H_0, then the random effects model is biased. The resulting parameter estimates are also not consistent if the initial observation of the dependent variable y_{it-1} and the unobserved individual effect η_i are correlated. This is the initial conditions problem, because y_{i0} is probably not the true starting point of the "process", just the start of our sample. In any case, y_{i0} is probably not randomly allocated but related to u_i as are the other y_{it}. If take-up behaviour in the initial year is indeed correlated with the time-invariant unobserved heterogeneity, as expected, failing to account for this unobserved individual heterogeneity will lead to an estimate of state dependency that is biased upwards. To address this issue, we follow Wooldridge's method of controlling for initial conditions by including in the specification the value of the dependent variable in the first wave – that is by conditioning on y_{i0} – and model the density of u_i conditional on $y_{i0}, \mathbf{x}_i$. This implies that u_i could be specified as:

$$u_i = \mu + \bar{\mathbf{x}}_i\boldsymbol{\delta} + \gamma_0 y_{i0} + \eta_i \tag{5}$$

where $\eta_i|\bar{\mathbf{x}}_i, y_{i0} \sim N(0, \sigma_\eta^2)$ and the latent regression can be expressed as follows:

$$y_{it}^* = \mu + \mathbf{z}_i\alpha + \mathbf{x}_{it}\beta + \gamma y_{it-1} + \bar{\mathbf{x}}_i\boldsymbol{\delta} + \gamma_0 y_{i0} + \eta_i + \varepsilon_{it} \tag{6}$$

Our dataset in the panel analysis comprises 16,491 unique eligible units for CB and 7,723 unique eligible units for LB/CB for the years 2011-2019. Due to changes in eligibility or attrition, some units drop out of the sample or join at a later wave during the period of analysis, making the dataset unbalanced. Restricting the analysis to a 9-wave balanced panel reduces sample size substantially to 6,817 and 3,297 respectively for CB and LB/UC, thereby reducing the precision of parameter estimates. Additionally, a balanced sample may not necessarily be a random sub-sample of all respondents because unobserved characteristics associated with attrition may also be associated with unobserved heterogeneity. We, therefore, opt for using the unbalanced panel for the regression analysis but perform robustness checks on the balanced panel.

UKHLS contains detailed income data as well as a broad range of demographic and labour market information. To better understand the factors influencing take-up, we include four types of explanatory variables in our analysis. The first group consists of individual-level variables that capture key characteristics of each respondent, such as age, gender, education, and original income. This group also includes personality traits, which are considered stable over time in which we use the measurements from the third wave, assuming they remain consistent thereafter. This method is akin to establishing an average personality trait for all years based on the data from the third wave. The second group of variables includes those at the eligible benefit-unit level, which takes the same value for each adult in the same benefit unit. Examples are the presence of dependent children in the benefit unit, household composition, housing tenure, as well as neighbourhood characteristics. The third set of variables are longitudinal means derived from the first two groups, used to implement the Mundlak-Chamberlain approach. Finally, we also control for time-fixed effects to take into account time trends.

The sign of the estimated parameters indicates the direction of the effect of the associated variables on the probability of taking up the benefit. However, due to the non-linearity of the model, determining the magnitude of the effects directly from the parameters is not straightforward. To address this issue, we follow the common practice of presenting marginal effects for benchmark individuals (such as "average" individuals with average characteristics). The marginal effect of an explanatory variable on the probability of take-up is, therefore, the change in the probability of take-up resulting from a one-unit change in the explanatory variable (if continuous) or a change from 0 to 1 (if it is a dummy variable), for an average individual.

For cross-sectional statistics and descriptive probit analysis, we use the UKMOD-UKHLS cross-sectional household weights. However, for longitudinal regressions, we use unweighted data. This is because it is not clear what the appropriate weight would be when multiple waves are pooled together - longitudinal weights are available for UKHLS data only for the original sample respondents who were interviewed at the first wave and at every wave up to and including the wave of interest. This means that using longitudinal weights would cause losing any individual who at some point dropped out of from the UKHLS, restricting the focus on the balanced sample. As a sensitivity test, we estimate weighted regressions to evaluate sensitivity to weighting, which may arise, for instance, if there are heterogeneous effects.[16] For this, we correct the UKHLS longitudinal weights by the inverse of the probability of being included in the estimation sample, estimated by a simple probit model. The estimates in the weighted models remained largely consistent.

6. ESTIMATION RESULTS

6.1 Take-up decisions

The dynamic model is estimated separately for CB and LB/UC. As mentioned earlier, the parameters are opaque to interpret due to the non-linearity of the model; we, therefore, present results as marginal effects for selected variables. (The original and full parameter estimates are available in the appendix for reference.) The results comparing CB and LB/UC take-up decisions highlight several notable differences.[17]

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[16] When the effect varies across subgroups within a population, the weighted regression accounts for this heterogeneity. However, when the variance in the characteristics that influence the effect is different across subgroups, the weighted regression may not yield an accurate estimate of the effect. See Solon et al., (2015) for a discussion of weighting.

[17] For comparison, we also estimated a simple pooled probit model, without controlling for individual effects. The estimated coefficients from the pooled probit regressions are discernibly different to those from the RE probit regressions, stressing the importance of unobserved heterogeneity (results are reported in Appendix B). When applying the correction suggested by Arulampalam (1999), the RE probit coefficients would differ by about 15%-25% on average (in absolute terms).

Table 4. Marginal effects on the probability of taking-up benefits, dynamic random effects probit model

	CB		LB/UC	
Lagged value of take-up	.163***	(.035)	.244***	(.033)
Initial Take-up	.191***	(.036)	.384***	(.042)
Log Simulated Eligible Amount	.002***	(.001)	.029***	(.005)
Age	.000	(.000)	.000	(.000)
Gender (Base: Female)				
Male	-.001	(.001)	.023**	(.010)
Marital Status (Base: Married/Cohabitating)				
Single	-.001	(.004)	.052***	(.019)
Separated, Divorced, Widowed	-.011	(.013)	.029	(.026)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African Asian	.001	(.004)	.013	.018
Asian or Asian British Chinese	.001	(.002)	.012	.011
Black or Black British	-.001	(.002)	-.019	.017
Arab and any other	-.012	(.002)	.009	.047
Health (Base: Not Disabled)				
Disabled	-.002	(.006)	.011	(.013)
Children in Household (Base: One)				
Two	-.001	(.002)	.045**	(.023)
Three or more	-.001	(.005)	.076***	(.025)
Minimum age of child in the household	-.006**	(.004)	-.035**	(.012)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	-.001	(.003)	.01	(.015)
Education (Non-Tertiary)				
Tertiary	-.001	(.001)	.001	(.007)
Number of rooms in a house	-.002***	(.001)	.002	(.006)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.001	(.001)	.011	(.016)
Rented	-.002	(.002)	.039***	(.010)
Reduced Rented	-.005	(.010)	.020	(.023)
Social Rented	.000	(.002)	.056***	(.009)
Free	-.003	(.007)	.058***	(.015)
Other	-.006	(.010)	-.0114	(.110)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	-.004	(.003)	-.018	(.026)
Technical and Skilled Roles	-.005	(.003)	-.004	(.019)
Service Manual and Support Roles	-.001	(.003)	.000	(.023)
Log of Original Income	.004*	(.003)	-.027**	(.011)
Neighbourhood effect	.001	(.012)	-.001	(.005)
Personality Traits				
Openness to Experience	.000	(.000)	-.003	(.004)

Conscientiousness	-.001	(.000)	-.004	(.004)
Extraversion	.000	(.001)	.004	(.003)
Agreeableness	.000	(.001)	-.001	(.004)
Neuroticism	.000	(.001)	.006	(.003)
Cognitive Ability	.000	(.001)	.004	(.004)
Standardized values of log simulated eligible amount	-.010***	(.011)	-.014	(.013)
Standardized values of neighbourhood effect	.000	(.014)	.009*	(.005)
Receipt of other benefits	.011***	(.003)	.049***	(.011)

Note: The table shows selected reported marginal effects of the results. The complete results can be found in Appendix B. Personality traits are only measured in the third wave and are assumed to remain constant, representing average traits for all years.

An important finding is the strong state dependence and persistence in take-up choices, in that current take-up behaviour is significantly affected by previous take-up decisions. The marginal effects of the lagged take-up choice suggest that past behaviour strongly influences present decisions (Table 4). Indeed, if an individual with an average set of characteristics and circumstances claimed CB in a given year, he or she would be 15.4 percentage points more likely to claim it in the following year (from 84.1% to 99.6%), if still eligible, with respect to a similar individual who did not claim. For LB/UC, the same figure is 24.4 percentage points more likely (from 71.7% to 97.1%). The results for CB take-up also reveal a significant drop in state dependency when a child turns 16. This is because parents must reapply to maintain eligibility.[18] Specifically, when the child is over 16, the take-up rate decreases by almost 20 percentage points, dropping from a near-perfect 99.6% to 80.8%.

The state dependency result is expected, and this dynamic is partly a consequence of the fact that, if circumstances remain unchanged, individuals typically remain enrolled without the need to re-apply. In such cases, transitions from take-up to non-take-up are few and likely to reflect measurement errors either in reported recipiency, simulated eligibility, or the observed circumstances themselves. Analysis of dynamic take-up is, however, still meaningful even when continued enrolment is automatic, given the possibility of transitions from non-take-up to take-up.

The estimated coefficients for the initial take-up demonstrate a significant positive effect for both benefits, indicating that eligible units are more likely to continue claiming the benefit if they initially claimed it. The significance also rejects the null hypothesis that initial conditional conditions are exogenous. The initial value of LB/UC take-up also implies that there is a substantial correlation between unobserved heterogeneity and the initial conditions. In fact, the coefficient on the initial value of take-up is positive and larger than the coefficient on the lagged value of take-up, suggesting that without

[18] For CB, parents must reapply to maintain eligibility when a child turns 16, if the child has left full-time non-advanced education or approved training and has registered for further education, work, or training with a careers service. Unsurprisingly, this is associated to a lower take-up (HM Revenue & Customs, 2023).

controlling for unobserved heterogeneity, the effect of state dependency would be significantly overestimated.

At first glance, results suggest that income-related factors have distinctive patterns for CB and LB/UC take-up decisions. For CB, income has a positive effect on take-up: a one-standard-deviation increase in the log of original income leads to a 0.2 percentage points increase in the probability of CB take-up. In contrast, LB/UC exhibits a negative coefficient: a one-standard-deviation increase in the log of original income results in a 2.9 percentage point decrease in the probability of LB/UC take-up.

However, for CB the effect of the time average of income, to control for unobserved heterogeneity, is negative. This implies that individuals with higher average income over time are less likely to apply for CB, with the marginal effect being a decrease of 1.0 percentage points. Consequently, the overall marginal effect of income on CB take-up is also negative. In contrast, average income is not significant for LB/UC. It is noteworthy that when also including all eligible units impacted by the HICBC, the negative effect of time-average income on CB take-up becomes notably pronounced, closer to 2 percentage points, aligning with *a priori* expectations, and the yearly income becomes insignificantly different from zero.

These findings suggest that CB appears more responsive to long-term “permanent” income. This may be because eligible units tend to have more stable income over time, given the broader eligibility nature of the benefit. Conversely, take-up for LB/UC demonstrates greater sensitivity to short-term income fluctuations.

Other income-related factors also play a role. For example, the number of rooms in the dwelling where individuals live, a proxy for financial wealth, shows a negative effect, indicating that households in larger dwellings are less likely to claim CB, everything else remaining constant. Additionally, the findings reveal distinct patterns for housing tenure categories. For CB, no clear effect emerges. However, for LB/UC, renters and individuals living in a subsidised accommodation exhibit a higher propensity for LB/UC participation than those who own their house on a mortgage. This suggests that rental accommodation (as well as social housing) might be associated with greater financial need that aligns with the purpose of LB/UC. Furthermore, we observe no differences between occupations.

Demographic factors such as gender and marital status exhibit distinct effects on take-up behaviour for the two benefits. For example, men are no more likely than women to claim CB, but significantly more likely to claim LB/UC. Being single does not affect the uptake of CB, but it increases the likelihood of claiming LB/UC. Having more children does not significantly affect CB take-up, but it increases the likelihood of claiming LB/UC. The minimum age of the youngest child in the household demonstrates consistent negative coefficients for both benefits, indicating that households with older children are less inclined to take up these benefits. Lack of significance of some possible determinants is also of interest. For instance, we do not find evidence of ethnic variability, as well as education. This might seem surprising at first, but can be rationalised by considering that the effect of these variables is at least partly mediated by income. Overall, these findings show that the mechanisms underlying take-up for the two benefits are very different, with financial needs – and related socio-demographic characteristics – playing a stronger role for LB/UC. This goes beyond the stricter means testing for LB/UC (results are conditional on eligibility), indicating that the design of the benefit has been to some extent over-internalised by the target population.

This seems to be true irrespective of psychological and intellectual characteristics: personality traits and cognitive skills do not have a direct effect on the take-up of benefits.

Neighbourhood effects are captured in our analysis by the average take-up rate in the local area district. From Table 4, we can observe that individual take-up is relatively higher in areas where more individuals are claiming the benefit. As already discussed, recent studies suggest that stigma decreases with local participation, indicating that peer evaluation influences individuals' concerns about their social image, leading to "positional externalities". As a result, the perceived disutility reduces as the number of peers who engage in the same behaviour increases. At the same time, social norms and imitative behaviour (which we can also consider as factors pertaining to the "mind"), as well as better information targeting on the part of the Government and knowledge sharing among communities (factors which we can better classify as pertaining to "matter", or material conditions), also play a role in lowering the barriers to claiming the benefits.

Considering the overall contribution of time-average variables (reported in the Appendix B), we observe that not all variables are individually statistically significant at conventional levels. However, a Wald test of the joint hypothesis that all the coefficients for time-averaged variables are equal to zero is rejected at 90% confidence interval for CB. The significance of time-averaged variables for LB/UC is stronger (hypothesis rejected at 95% confidence interval). In the context of the Mundlak (1978) approach, the significance of a time-averaged variable implies that the unobserved heterogeneity it captures has a systematic impact on the outcome variable. This shows the importance of incorporating time-averaged variables to account for individual-specific characteristics that may not be directly observable but still influence the take-up decision. Thus, the significance of the time-averaged variables implies that not accounting for unobserved heterogeneity in the random-effect model would result in biased estimates.[19]

The parameter ρ measures the proportion of the total variance in take-up rates due to variability between sampling units of individuals with different observed characteristics. Our estimate for ρ, close to 0.4 for both benefits, suggest that a substantial proportion of the total variance in the take-up process is within individuals sharing the same observed characteristics, indicating that the contribution of unobserved heterogeneity is substantial.

[19] The results produced in the Appendix B confirm that the exclusion of time-averaged variables would result in an upward bias of the estimates.

6.2 State Dependency in Benefit Recipiency

To further characterise the role of state dependency, we generate a set of predicted patterns for the dependent variable over time, using the model's estimates. This describes the asymptotic inflows and outflows into benefit recipiency in a hypothetical scenario where individual characteristics remained unchanged.

As indicated in Table 5, the positive state dependency implies a high persistence probability and a low exit probability. The entry rate for CB is 0.80, while for LB/UC, it is slightly lower at 0.68. Both benefit groups exhibit nearly perfect persistence and a high long-term steady-state probability.

Table 5. Asymptotic inflows and outflows into benefit recipiency

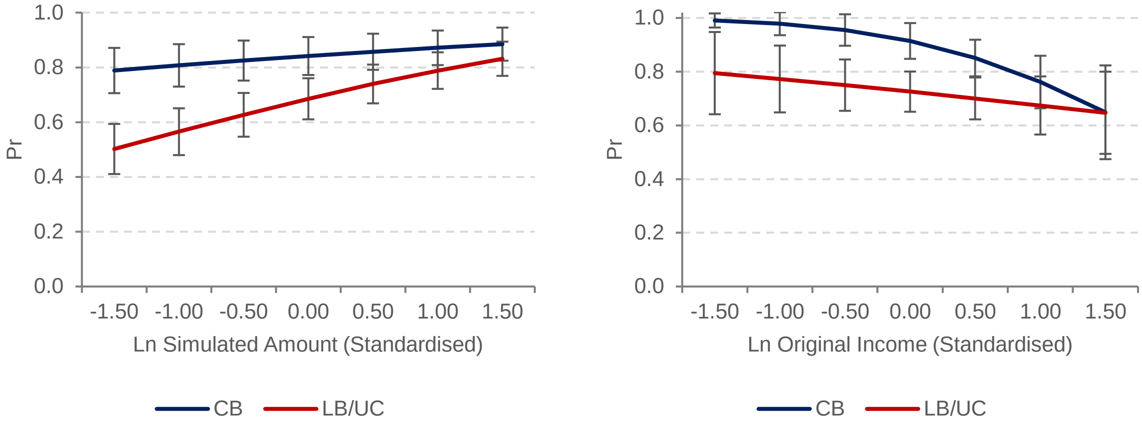
	CB		LB/UC	
Entry Probability (1|0)	.795***	(.030)	.678***	(.024)
Persistence Probability (1|1)	.981***	(.002)	.896***	(.005)
Exit Probability (0|1)	.019***	(.002)	.332***	(.024)

*Note: Standard errors are shown in parentheses. * p < .10, ** p < .05, *** p < .01. The numbers reported are the average predicted probabilities.*

We assess the role of state dependence on an individual's take-up and its effect across the different amounts of eligibility and original income (in real terms). The margins plots in Figure 5 reveal a clear trend for an individual with an average set of characteristics. As the benefit amount increases, the likelihood of individuals claiming the benefits also increases. This positive relationship shows that higher benefit amounts serve as incentives, encouraging more people to participate and increasing the opportunity cost of not claiming the benefits.

The role of material factors is also demonstrated through the original income. The entry probability for CB is notably higher than LB/UC. As income levels increase, we observe a decrease in the entry probabilities for both CB and LB/UC. However, the change in entry probability for LB/UC appears less sensitive to income in comparison to CB. This indicates that the entry probability for CB gradually approaches that of LB/UC at relatively higher income levels.

Figure 5. Entry probability by eligibility amount and original income



Note: The figures present the take-up probability, conditional on non-take-up in the previous period. The numbers reported are the predicted probabilities evaluated at the mean of the covariates. The error bars represent the 95% confidence interval bars. Income is standardised at the average level of real income across all waves.

6.3 Robustness Check for Measurement Error

We further test how sensitive our results are with respect to different assumptions concerning measurement errors. As explained earlier, in the baseline analysis we adopt a broad definition of eligibility, which include individuals who are not simulated to be eligible but still receive benefits. If measurement errors are present and non-random, including these individuals in the analysis could potentially lead to significant changes in the reported results. As a robustness, we replicate the analysis excluding such individuals. Results exhibit only minimal deviations with respect to the baseline (see Appendix B).

6.4 The break-even point of claiming benefit

The economic interpretation of non-take-up points to the implicit or explicit take-up costs – material costs, information costs, psychological costs – being higher than the benefits – the extra income generated by the benefit. Along these lines, based on our estimates we can compute, for each eligible individual, the probability of take-up associated to different levels of the benefit. The amount associated to a probability of 50% can then be interpreted as the break-even point of claiming the benefit: at that amount, an individual is indifferent between claiming and non-claiming. Said differently, the break-even point represents the expected benefit amount required to offset implicit costs associated with claiming the benefit.

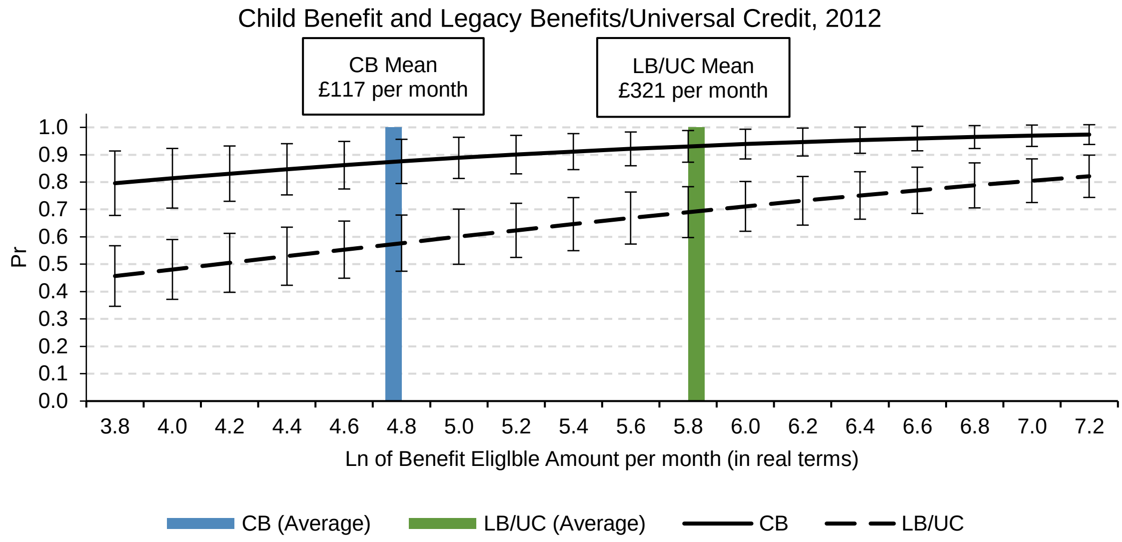
The margins plot depicting the probability of individuals opting for both types of benefits as a function of the eligible amount (in real terms) reveals a clear trend, when fixing all other variables at their means (cf. Figure 6). As the entitlement amount increases, there is a corresponding rise in the likelihood of individuals choosing to claim the benefits. This positive relationship signifies that higher benefit amounts serve as incentives, encouraging more individuals to participate and increasing the opportunity cost of not claiming the benefits.

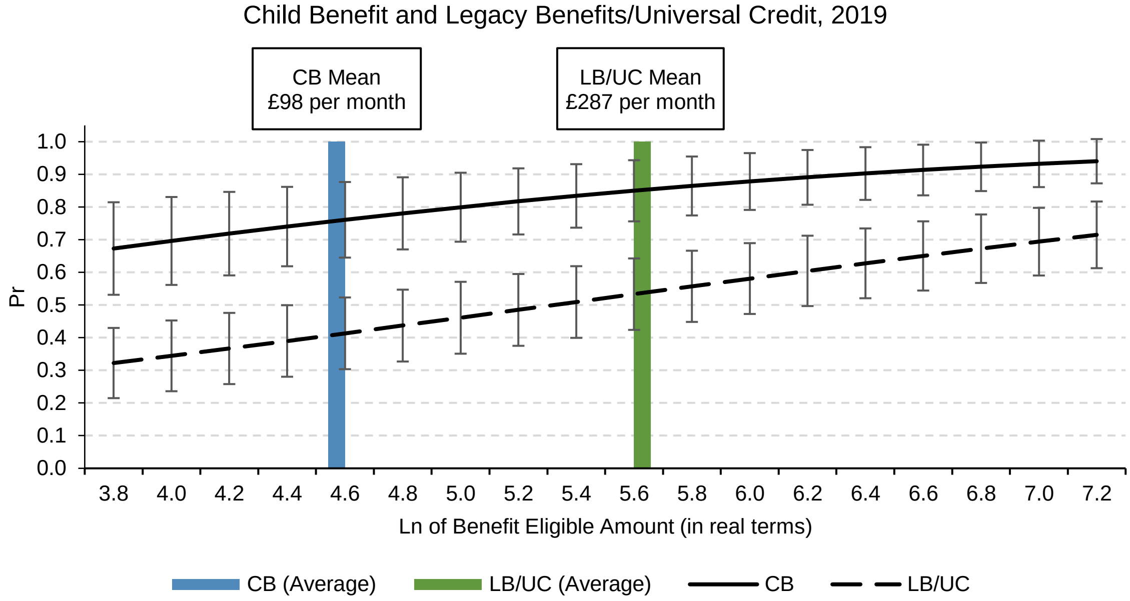
In both 2012 and 2019, the likelihood of claiming the CB was notably higher than LB/UC across all entitlement levels. However, the probabilities of claiming the CB were lower in 2019 compared to 2012. This decrease is statistically significant at the 95% confidence level and coincides with a reduction in the average eligible benefits CB amount during this period.

Shifting to LB/UC, in 2012, it took £800 per year (in real terms) to push the probability of take-up just above 50%. Given that the average eligible amount was £3,846 per year, this indicates that the “average” individual obtained a net utility gain from claiming the benefit. In 2019, the entitlement amount to attain a 50% probability of claiming the benefits rose to £2,657 per year (in real terms). To contextualise, the 2019 average eligible payments were £3,446 per year, implying that the average payment deteriorated at 2010 prices. The higher threshold associated with LB/UC compared to CB suggests the possibility of greater implicit costs in claiming these benefits compared to CB. Furthermore, we observe that in 2019, the probability of claiming LB/UC was significantly lower at each level of entitlement than in 2012.

The increasing implicit cost suggests that the decline in take-up rates is not solely due to the decrease in the real value of the benefits. Starting with CB, the introduction of the HICBC has contributed to the rise in the implicit cost of claiming CB, particularly for higher-income parents. The static threshold for HICBC implies that as wages increase with inflation, more parents become subject to the charge, leading to a higher administrative burden. The increase in implicit costs is more evident in the case of LB/UC, indicating that take-up rates are influenced not only by the real value of the benefits but also by increasing administrative complexities. Confusion about eligibility, fear of penalties, misunderstanding of migration notices, and assumptions about automatic transfers (from LB to UC) have also contributed to increased costs and barriers associated with claiming benefits. The higher implicit costs of claiming LB/UC could also reflect social barriers, including a sense of stigma, that can stop citizens from applying.

Figure 6. Predicted probabilities of take-up





Note: The figures present the take-up probability, conditional on non-take-up in the previous period. The numbers reported are the predicted probabilities evaluated at the mean of the covariates. The error bars represent the 95% confidence interval bars. Base year for prices is 2010.

7. DISCUSSION AND CONCLUSION

This paper has studied the take-up rate and the economic and psychological factors influencing take-up rates for Child Benefit and Legacy Benefits / Universal Credit, two of the main welfare programs in the UK. Using a dynamic model estimated on panel data, we reveal that unobserved characteristics of eligible individuals influence the probability of taking up benefits. We also show evidence of strong state dependency, where past claiming behaviour affects current take-up.

Our analysis suggests that whether or not to take up a particular benefit is primarily influenced by economic factors, namely the amount of benefit an individual is entitled to and their original income. This indicates that the financial implications of the decision are the most crucial determinants of take-up. Interestingly, we have found no significant effect of personality traits or cognitive skills on the take-up decision, which suggests a subordination of “mind” versus “matter” in explaining claiming behaviour. This is an important finding as it emphasises the role of economic incentives in shaping the behaviour of individuals when it comes to accessing social benefits. It also corroborates the common approach in the (economic) literature of disregarding psychological factors, often grounded in data availability.

The results also reveal that individual take-up is affected by the average take-up in the local area. This factor may reflect a combination of matter and mind factors that work in the same direction: decreased stigma, accommodating social norms, emulating behaviour, and improved access to information within communities.

The findings may not come as a surprise, but they may have important implications for related policies. In particular, the strong persistence in take-up behaviour, as well as spillovers within local communities, suggest focussing efforts towards facilitating first-time claims in more deprived areas. This could be done with a combination of financial measures (e.g. a “first claim bonus”) to increase perceived gains, administrative/communication actions (e.g. “claim workshops”) and collaboration among key stakeholders (e.g. working with non-governmental organisations like trade unions and employers) to lower associated costs. Additionally, automatic enrolment, eliminating the need for applications, could enhance claim rates, particularly for benefits with minimal administrative complexities.

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APPENDIX A

Measures of Personality Traits

In Wave 3, the UKHLS dataset contains a battery of items to measure personality traits using the 15-item version of the Big Five Inventory (John et al., 1991), employing a Likert scale ranging from 1 (“disagree strongly”) to 5 (“agree strongly”). The precise set of questions asked to participants is detailed in Table A.1. “R” is used to indicate reversed values. The short version of the Big Five is considered to be as a valid measure of the Big Five personality traits, with good reliability (Hahn et al., 2012; Soto & John, 2017).

Table A.1: BFI-S Items, pre-selected set of items

Openness to Experience	scptrt5o1	I see myself as someone who is original, comes up with new ideas.	
	scptrt5o2	I see myself as someone who values artistic, aesthetic experiences.	
	scptrt5o3	I see myself as someone who has an active imagination.	
Conscientiousness	scptrt5c1	I see myself as someone who does a thorough job.	
	scptrt5c2	I see myself as someone who tends to be lazy.	R
	scptrt5c3	I see myself as someone who does things efficiently.	
Extraversion	scptrt5e1	I see myself as someone who is talkative.	
	scptrt5e2	I see myself as someone who is outgoing, sociable.	
	scptrt5e3	I see myself as someone who is reserved.	R
Agreeableness	scptrt5a1	I see myself as someone who is sometimes rude to others.	R
	scptrt5a2	I see myself as someone who has a forgiving nature.	
	scptrt5a3	I see myself as someone who is considerate and kind to almost everyone.	
Neuroticism	scptrt5n1	I see myself as someone who worries a lot.	
	scptrt5n2	I see myself as someone who gets nervous easily.	
	scptrt5n3	I see myself as someone who is relaxed, handles stress well.	R

An Exploratory Factor Analysis (EFA) was applied to reduce multiple items to a common factor. EFA was carried out using principal factor components and Bartlett scores. The results are presented in Tables A.2-A.7.

Table A.2: The factor loadings for Openness to Experience

	Openness to Experience		
	Loadings	Communalities	Specific Variance
Variable	λ_j	h_j^2	ψ_j
scptrt5o1	.79	.63	.37
scptrt5o2	.73	.53	.47
scptrt5o3	.81	.66	.34
Variance accounted for	1.815	1.815	
Proportion of total variance	.605		

Cumulative proportion	.605		

Table A.3: The factor loadings for Conscientiousness

	Conscientiousness		
	Loadings	Communalities	Specific Variance
Variable	λ_j	h_j^2	ψ_j
scptrt5c1	.79	.63	.37
scptrt5c2	-.51	.27	.73
scptrt5c3	.82	.68	.32
Variance accounted for	1.569	1.569	
Proportion of total variance	.523	.523	
Cumulative proportion	.523		

Table A.4: The factor loadings for Extraversion

	Extraversion		
	Loadings	Communalities	Specific Variance
Variable	λ_j	h_j^2	ψ_j
scptrt5e1	.83	.68	.32
scptrt5e2	.82	.66	.34
scptrt5e3	-.56	.31	.69
Variance accounted for	1.656	1.656	
Proportion of total variance	.552	.552	
Cumulative proportion	.552		

Table A.5: The factor loadings for Agreeableness

	Agreeableness		
	Loadings	Communalities	Specific Variance
Variable	λ_j	h_j^2	ψ_j
scptrt5a1	-.58	.32	.68
scptrt5a2	.78	.60	.40
scptrt5a3	.82	.67	.33
Variance accounted for	1.600	1.600	
Proportion of total variance	.533	.533	
Cumulative proportion	.533		

Table A.6: The factor loadings for Neuroticism

	Neuroticism		
	Loadings	Communalities	Specific Variance
Variable	λ_j	h_j^2	ψ_j
scptrt5n1	.84	.70	.30
scptrt5n2	.80	.64	.36
scptrt5n3	-.71	.51	.49
Variance accounted for	1.858	1.858	
Proportion of total variance	.619	.619	

Cumulative proportion	.619		

Table A.7: The factor loadings for Cognitive Ability

	Cognitive Ability		
	Loadings	Communalities	Specific Variance
Variable	λ_j	h_j^2	ψ_j
cgvfc	.48	.79	.21
cgna	.52	.91	.09
cgs7ca	.50	.85	.15
cgwri	.49	.82	.18
Variance accounted for	3.372	3.372	
Proportion of total variance	.843	.843	
Cumulative proportion	.843		

APPENDIX B

Association with individual characteristics

In order to better understand how characteristics of eligible units are associated with take-up behaviour, we present results from a probit model of take-up for CB and LB/UC, estimated on pooled data for all years of analysis, except 2010 (Table 2).[20] The most prominent economic features that predict take-up are the eligible amount and the gross income of the eligible unit. As expected, the higher the eligible amount and the lower the original income, the greater the take-up rate. When it comes to psychological factors, the personality traits do not have a significant relationship with take-up. When examining the interaction effects by gender, we observe that personality traits do not show a significant correlation with CB take-up. We also find that conscientiousness is negatively associated with LB/UC take-up for females, whereas for males, conscientiousness is positively correlated with LB/UC take-up.

Turning to demographics, we observe an inverse U-shaped relationship between age and CB take-up. On average, men tend to display higher take-up for LB/UC and a slightly lower take-up for CB as compared to women, but the difference for the latter is not significant. For CB, being separated, divorced, or widowed is associated with a significantly lower take-up as compared to being married or cohabitating. However, the reverse is true for LB/UC, probably because of the higher rates for couples. In addition, certain ethnic groups, such as Chinese, Black, and Arab, have a lower tendency to claim benefits than White. A higher take-up of benefits is associated with households having more children. Those who claim CB benefits usually have younger children as compared to those who claim LB/UC. Living in certain regions, such as London, is associated with significantly lower take-up rates.

Socio-economic status is an important factor that can demonstrate both economic and psychological aspects. Individuals with tertiary education are less likely to take up benefits. People in service, manual, and support roles are more likely to seek benefits compared to those in higher-status occupations. However, the take-up rate for CB is more evenly distributed across occupations, as eligibility is not heavily reliant on the means test aspect. All this is of course *ceteris paribus*, and in particular conditional on income.

Table B.1. Estimates from a probit model of take-up, all years

	CB		LB/UC	
Log Simulated Eligible Amount	.173***	(.020)	.281***	(.017)
Age	.040*	(.023)	.012	(.013)
Age2	-.001**	(.000)	-.000	(.000)

[20] Except 2010 because personality traits and cognitive ability are not recorded for that year. Since personality traits are largely stable, we utilise the recordings from the third wave and assume they remain the same thereafter.

Gender (Base: Female)				
Male	-.042	(.053)	.293***	(.046)
Marital Status (Base: Married/Cohabitating)				
Single	-.034	(.063)	.098**	(.039)
Separated, Divorced, Widowed	-.304***	(.079)	.370***	(.047)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean	-.136	(.154)	-.143	(.101)
Asian or Asian British Chinese	-.447***	(.074)	.048	(.054)
Black or Black British	-.466***	(.122)	-.255***	(.068)
Arab and any other	-.515***	(.193)	.435*	(.231)
Health (Base: Not Disabled)				
Disabled	-.007	(.155)	.402***	(.105)
Children in Household (Base: One)				
Two	.097**	(.048)	.226***	(.034)
Three or more	.151*	(.080)	.616***	(.050)
Minimum age of the child in the household	-.011**	(.005)	.019***	(.004)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	-.051	(.041)	.041	(.034)
Education (Non-Tertiary)				
Tertiary	-.120**	(.050)	-.176***	(.033)
Number of rooms in the dwelling	-.184***	(.039)	-.144***	(.031)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.084	(.074)	.090*	(.051)
Rented	-.215***	(.070)	.325***	(.041)
Reduced Rented	-.524***	(.153)	.163	(.159)
Social Rented	-.054	(.082)	.666***	(.046)
Free	-.016	(.230)	.797***	(.173)
Other	-.586	(.433)	.268	(.366)
Labour Market Status (Base: Inactive)				
Professional and Managerial Roles	.464***	(.152)	-.073	(.082)
Technical and Skilled Roles	.519***	(.146)	.202***	(.075)
Service Manual and Support Roles	.732***	(.155)	.376***	(.079)
Log of Original Income (standardised)	-.150**	(.066)	-.306***	(.053)
Neighbourhood effect (standardised)	.064***	(.021)	.811***	(.184)
Personality Traits				
Openness to Experience	.003	(.027)	-.016	(.017)
Conscientiousness	-.035	(.027)	-.015	(.017)
Extraversion	-.018	(.026)	.013	(.016)
Agreeableness	.006	(.026)	.028*	(.016)
Neuroticism	.016	(.025)	.079***	(.016)
Cognitive Ability	-.026	(.026)	-.007	(.018)
Receipt of LB/UC (Base: Not in receipt)				
Receipt	.985***	(.077)	.491***	(.041)
Time Effects (Base: 2011)				
2012	.047	(.051)	-.255***	(.051)
2013	-.112**	(.052)	-.341***	(.052)
2014	-.157***	(.057)	-.383***	(.055)
2015	-.184***	(.057)	-.495***	(.056)
2016	-.200***	(.058)	-.557***	(.058)
2017	-.184***	(.062)	-.598***	(.060)
2018	-.336***	(.062)	-.657***	(.065)
2019	-.410***	(.067)	-.877***	(.069)
Constant	.749	(.471)	-.329	(.285)

Observations	22,395		12,607	
Wald chil2(50)	622.07		2,191.79	
Prob > chi2	.000		.000	

*Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors are in the brackets.*

As for neighbourhood effects, the descriptive analysis presented in Table 2 indicates that eligible units residing in neighbourhoods with higher take-up rates are more likely to claim social benefits.

Additionally, the correlations indicate that individuals who claim other benefits are more likely to claim the benefits under study. Furthermore, the probit analysis confirms the gradual decline in take-up rates over the years.

Dynamic Model Results

Table B2. Probability of Claiming CB and LB/UC, dynamic random-effects probit model

	CB		LB/UC	
Lagged value of take-up	1.785***	(.107)	1.328***	(.084)
Initial take-up	1.726***	(.176)	1.699***	(.152)
Log Simulated Eligible Amount	.133***	(.028)	.318***	(.038)
Age	-.069*	(.038)	-.017	(.029)
Age2	.001*	(.000)	.000	(.000)
Gender (Base: Female)				
Male	-.049	(.079)	.248**	(.109)
Marital Status (Base: Married/Cohabitating)				
Single	-.056	(.249)	.539***	(.177)
Separated, Divorced, Widowed	-.477	(.347)	.255	(.231)
Ethnicity (Base: White)				
Mixed: White and Black	.067	(.245)	.150	(.241)
Asian or Asian British Chinese	.047	(.135)	.146	(.142)
Black or Black British	-.047	(.172)	-.170	(.135)
Arab and any other	-.415	(.406)	.099	(.590)
Disability (Base: Not Disabled)				
Disabled	-.109	(.221)	.160	(.178)
Children in Household (Base: One)				
Two	-.115	(.421)	.354**	(.162)
Three or more	-.113	(.484)	.825***	(.271)
Minimum age of the child in the household (standardised)	-.392***	(.150)	-.368***	(.136)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	-.049	(.156)	.105	(.151)
Education (Non-Tertiary)				
Tertiary	-.053	(.069)	.010	(.080)
Number of rooms in the dwelling	-.151***	(.046)	.043	(.065)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.034	(.107)	.081	(.126)
Rented	-.088	(.103)	.351***	(.097)
Reduced Rented	-.274	(.352)	.160	(.220)
Social Rented	.029	(.123)	.624***	(.105)
Free	-.179	(.297)	.643**	(.306)
Other	-.371	(.480)	-.075	(.678)
Labour Market Status (Base: Inactive)				
Professional and Managerial Roles	-.301	(.332)	-.238	(.276)
Technical and Skilled Roles	-.357	(.329)	-.097	(.231)
Service Manual and Support Roles	-.114	(.407)	.043	(.288)
Log of Original Income (standardised)	.236*	(.132)	-.287**	(.122)
Neighbourhood effect (standardised)	.080*	(.045)	-.009	(.053)
Personality Traits				
Openness to Experience	-.008	(.040)	-.031	(.039)
Conscientiousness	-.045	(.041)	-.042	(.041)
Extraversion	-.009	(.035)	.042	(.038)
Agreeableness	.016	(.036)	.004	(.040)
Neuroticism	-.007	(.038)	.060	(.038)

Cognitive Ability	-.020	(.037)	.046	(.042)
Receipt of other benefits	.807***	(.122)	.475***	(.092)
Lagged value of take-up # Child aged 16	-.449***	(.162)		
Time Effects (Base: 2011)				
2012	.379**	(.157)	.353**	(.149)
2013	.079	(.141)	.508***	(.145)
2014	.248*	(.139)	.512***	(.140)
2015	.187	(.130)	.394***	(.139)
2016	.217*	(.120)	.410***	(.137)
2017	.287**	(.118)	.318**	(.136)
2018	.063	(.123)	.158	(.131)
Time-averaged characteristics				
Responsible for housing costs	-.000	(.167)	-.171	(.172)
Married, Cohabitating	.065	(.262)	.655***	(.198)
Separated, Divorced, Widowed	.404	(.403)	.515**	(.238)
Two children in household	-.122	(.181)	-.291	(.184)
Three or more children in household	-.084	(.287)	-.320	(.286)
Minimum age of child in household	.242	(.168)	.434***	(.152)
Professional and Managerial Roles	.819*	(.452)	.102	(.343)
Technical and Skilled Roles	1.038**	(.444)	.254	(.301)
Service Manual and Support Roles	.998**	(.515)	.169	(.351)
Log of Original Income (standardised)	-.639***	(.236)	-.148	(.144)
Neighbourhood effect (standardised)	.001	(.048)	.093*	(.056)
Constant	.092	(.953)	-2.473***	(.653)
/				
variance	.547***	(.112)	.671***	(.135)
rho	.368		.401	
Observations	16,009		7,723	

*Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors are in the brackets.*

Table B3. Probability of Claiming CB, dynamic probit model

	(1)	(2)	(3)	(4)
Estimation Sample	Pooled Probit	RE-Probit	RE-Probit	Wooldridge
Log Simulated Eligible Amount	.102***	.110***	.198***	.133***
	(.023)	(.025)	(.025)	(.028)
Age	-.038	-.041	-.058	-.069*
	(.027)	(.030)	(.037)	(.038)
Age2	.000	.000	.001	.001*
	(.000)	(.000)	(.000)	(.000)
Gender (Base: Female)				
Male	-.030	-.032	-.096	-.049
	(.060)	(.065)	(.076)	(.079)
Marital Status (Base: Married/Cohabitating)				
Single	-.032	-.031	-.064	-.056
	(.206)	(.217)	(.085)	(.249)
Separated, Divorced, Widowed	-.314	-.322	-.199*	-.477
	(.277)	(.295)	(.112)	(.347)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean	.040	.021	-.110	.067
	(.168)	(.182)	(.230)	(.245)
Asian or Asian British Chinese	-.106	-.134	.088	.047
	(.090)	(.097)	(.129)	(.135)
Black African Asian	-.117	-.141	-.041	-.047
	(.128)	(.139)	(.159)	(.172)
Arab and any other	-.438*	-.480*	-.322	-.415
	(.257)	(.277)	(.403)	(.406)
Health (Base: Not Disabled)	.000	.000	.000	.000
Disabled	-.033	-.018	-.113	-.109
	(.174)	(.188)	(.223)	(.221)
Children in Household (Base: One)				
Two	.197	.237	-.304	-.115
	(.290)	(.309)	(.416)	(.421)
Three or more	.168	.227	-.326	-.113
	(.351)	(.376)	(.426)	(.484)
Minimum age of child in household	-.154	-.172	-.128***	-.392***
	(.120)	(.128)	(.046)	(.150)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	-.028	-.025	-.052	-.049
	(.116)	(.126)	(.059)	(.156)
Education (Non-Tertiary)	(.)	(.)	(.)	(.)
Tertiary	-.045	-.060	-.151**	-.053
	(.052)	(.057)	(.065)	(.069)
Number of rooms in a house	-.128***	-.138***	-.205***	-.151***
	(.035)	(.038)	(.046)	(.046)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.056	.068	.124	.034
	(.079)	(.087)	(.104)	(.107)
Rented	-.098	-.108	-.104	-.088
	(.077)	(.083)	(.100)	(.103)
Reduced Rented	-.335	-.385*	-.302	-.274

	(.210)	(.226)	(.328)	(.352)
Social Rented	.020	.018	-.034	.029
	(.087)	(.094)	(.124)	(.123)
Free	-.121	-.146	.112	-.179
	(.214)	(.232)	(.318)	(.297)
Other	-.079	-.028	-.404	-.371
	(.375)	(.389)	(.476)	(.480)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	-.240	-.259	.378**	-.301
	(.261)	(.278)	(.173)	(.332)
Technical and Skilled Roles	-.219	-.237	.557***	-.357
	(.253)	(.269)	(.170)	(.329)
Service Manual and Support Roles	-.054	-.064	.838***	-.114
	(.313)	(.336)	(.190)	(.407)
Log of Original Income	.197*	.218*	-.471***	.236*
	(.106)	(.112)	(.129)	(.132)
Neighbourhood effect	.070*	.073*	.095***	.080*
	(.037)	(.040)	(.029)	(.045)
Personality Traits				
Openness to Experience	-.014	-.013	.002	-.008
	(.030)	(.032)	(.037)	(.040)
Conscientiousness	-.031	-.039	-.028	-.045
	(.030)	(.032)	(.038)	(.041)
Extraversion	-.007	-.005	-.003	-.009
	(.027)	(.029)	(.034)	(.035)
Agreeableness	.010	.012	.032	.016
	(.026)	(.028)	(.034)	(.036)
Neuroticism	-.001	-.000	.007	-.007
	(.027)	(.029)	(.035)	(.038)
Cognitive Ability	-.025	-.025	-.011	-.020
	(.028)	(.031)	(.036)	(.037)
Receipt of LB/UC (Base: Not in receipt)				
Receipt	.700***	.764***	.854***	.807***
	(.093)	(.107)	(.123)	(.122)
Time Effects (Base: 2011)				
2012	.308**	.325**	.266**	.379**
	(.124)	(.133)	(.112)	(.157)
2013	.048	.063	.029	.079
	(.113)	(.122)	(.107)	(.141)
2014	.218*	.246**	.222**	.248*
	(.111)	(.121)	(.112)	(.139)
2015	.203*	.210*	.146	.187
	(.106)	(.115)	(.112)	(.130)
2016	.160	.175*	.293**	.217*
	(.098)	(.105)	(.115)	(.120)
2017	.218**	.241**	.335***	.287**
	(.095)	(.104)	(.120)	(.118)
2018	.038	.040	.111	.060
	(.102)	(.111)	(.125)	(.123)
Time-average variables				
Responsible for housing costs	-.005	-.012		.000

	(.124)	(.134)		(.167)
Single	.026	.036		.065
	(.215)	(.227)		(.262)
Separated, Divorced, Widowed	.202	.205		.404
	(.335)	(.352)		(.403)
Two	-.028	-.030		-.122
	(.142)	(.152)		(.181)
Three or more	.046	.028		-.084
	(.230)	(.247)		(.287)
Minimum age of child in household	.047	.054		.242
	(.136)	(.145)		(.168)
Professional and Managerial Roles	.640*	.721**		.819*
	(.333)	(.354)		(.452)
Technical and Skilled Roles	.722**	.811**		1.038**
	(.324)	(.344)		(.444)
Service Manual and Support Roles	.718*	.823**		.998*
	(.379)	(.406)		(.515)
Log of Original Income	-.407**	-.451**		-.639***
	(.181)	(.194)		(.236)
Neighbourhood effect	-.002	.004		.001
	(.039)	(.042)		(.048)
Lagged value of take-up	2.326***	2.285***	1.804***	1.785***
	(.084)	(.094)	(.102)	(.107)
Age of Child is 16	.352	.342	.267	.272
	(.265)	(.282)	(.411)	(.387)
Lagged value of take-up x Age of Child is 16	-.188	-.143	-.532***	-.449***
	(.131)	(.143)	(.154)	(.162)
Initial take-up			1.673***	1.726***
			(.167)	(.176)
Constant	-.192	-.065	.231	.092
	(.678)	(.726)	(.914)	(.953)
/				
var(_cons[idperson])		.157**	.570***	.547***
		(.065)	(.107)	(.112)
Observations	16009	16009	16149	16009
ll	-1977.488	-1972.162	-2146.425	-1862.800
Wald test	1785	1438	1050	985
p	.000	.000	.000	.000
rho		.136	.363	.354

*Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors are in the brackets.*

Table B4. Probability of Claiming LB/UC, dynamic probit model

	(1)	(2)	(3)	(4)
	Pooled Probit	RE- Probit	RE-Probit	Wooldridge
Log Simulated Eligible Amount	.258***	.280***	.321***	.318***
	(.027)	(.030)	(.038)	(.038)
Age	.003	.001	-.006	-.017
	(.021)	(.022)	(.029)	(.029)
Age2	-.000	-.000	.000	.000
	(.000)	(.000)	(.000)	(.000)
Gender (Base: Female)	.000	.000	.000	.000
Male	.218***	.242***	.209**	.248**
	(.077)	(.084)	(.104)	(.109)
Marital Status (Base: Married/Cohabitating)				
Single	.343**	.389**	.010	.539***
	(.151)	(.160)	(.087)	(.177)
Separated, Divorced, Widowed	.208	.224	.144	.255
	(.188)	(.201)	(.104)	(.231)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African Asian	.185	.188	.176	.150
	(.173)	(.189)	(.246)	(.241)
Asian or Asian British Chinese	.035	.039	.184	.146
	(.093)	(.101)	(.140)	(.142)
Black or Black British	-.214**	-.236**	-.189	-.170
	(.095)	(.104)	(.132)	(.135)
Arab and any other	.183	.214	.110	.099
	(.395)	(.456)	(.566)	(.590)
Health (Base: Not Disabled)				
Disabled	.145	.159	.176	.160
	(.155)	(.163)	(.176)	(.178)
Children in Household (Base: One)	.000	.000	.000	.000
Two	.224*	.259*	.157**	.354**
	(.126)	(.135)	(.080)	(.162)
Three or more	.439**	.513**	.594***	.825***
	(.209)	(.224)	(.120)	(.271)
Minimum age of child in household	-.214**	-.225**	-.028	-.368***
	(.096)	(.103)	(.050)	(.136)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	.016	.019	-.033	.105
	(.115)	(.123)	(.074)	(.151)
Education (Non-Tertiary)	.000	.000	.000	.000
Tertiary	.005	-.002	-.002	.010
	(.055)	(.060)	(.079)	(.080)

Number of rooms in dwelling	-.017	-.027	.043	.043
	(.040)	(.043)	(.067)	(.065)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.068	.080	.099	.081
	(.088)	(.096)	(.125)	(.126)
Rented	.269***	.306***	.352***	.351***
	(.066)	(.075)	(.096)	(.097)
Reduced Rented	.016	.039	.130	.160
	(.190)	(.205)	(.226)	(.220)
Social Rented	.448***	.513***	.635***	.624***
	(.071)	(.084)	(.104)	(.105)
Free	.416*	.438*	.625**	.643**
	(.238)	(.257)	(.300)	(.306)
Other	-.085	-.061	-.268	-.075
	(.493)	(.540)	(.664)	(.678)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	.023	.007	-.222	-.238
	(.211)	(.224)	(.190)	(.276)
Technical and Skilled Roles	.105	.091	.053	-.097
	(.179)	(.191)	(.177)	(.231)
Service Manual and Support Roles	.278	.259	.125	.043
	(.220)	(.236)	(.182)	(.288)
Log of Original Income	-.207**	-.213**	-.392***	-.287**
	(.098)	(.104)	(.104)	(.122)
Neighbourhood effect	-.005	-.010	.056	-.009
	(.041)	(.045)	(.035)	(.053)
Personality Traits				
Openness to Experience	-.013	-.014	-.029	-.031
	(.027)	(.030)	(.038)	(.039)
Conscientiousness	-.034	-.036	-.041	-.042
	(.029)	(.031)	(.041)	(.041)
Extraversion	.025	.030	.040	.042
	(.027)	(.030)	(.038)	(.038)
Agreeableness	.025	.027	.010	.004
	(.027)	(.029)	(.040)	(.040)
Neuroticism	.048*	.056**	.063*	.060
	(.026)	(.028)	(.037)	(.038)
Cognitive Ability	.027	.027	.040	.046
	(.029)	(.032)	(.042)	(.042)
Receipt of CB (Base: Not in receipt)				
Receipt	.371***	.403***	.453***	.475***
	(.067)	(.075)	(.089)	(.092)
Time-Effects				

2012	.172	.219*	.579***	.353**
	(.107)	(.116)	(.128)	(.149)
2013	.361***	.415***	.696***	.508***
	(.108)	(.117)	(.129)	(.145)
2014	.372***	.420***	.686***	.512***
	(.106)	(.114)	(.129)	(.140)
2015	.283***	.318***	.525***	.394***
	(.105)	(.114)	(.132)	(.139)
2016	.271**	.308***	.521***	.410***
	(.106)	(.115)	(.132)	(.137)
2017	.193*	.220*	.398***	.318**
	(.105)	(.114)	(.136)	(.136)
2018	.054	.075	.208	.158
	(.106)	(.113)	(.130)	(.131)
Time-average variables				
Responsible for housing costs	-.044	-.049		-.171
	(.130)	(.139)		(.172)
Single	.426**	.460***		.655***
	(.166)	(.175)		(.198)
Separated, Divorced, Widowed	.329*	.387*		.515**
	(.193)	(.208)		(.238)
Two	-.154	-.168		-.291
	(.140)	(.150)		(.184)
Three or more	-.037	-.052		-.320
	(.220)	(.235)		(.286)
Minimum age of child in household	.287***	.302***		.434***
	(.108)	(.116)		(.152)
Professional and Managerial Roles	-.191	-.221		.102
	(.267)	(.283)		(.343)
Technical and Skilled Roles	-.036	-.032		.254
	(.237)	(.251)		(.301)
Service Manual and Support Roles	-.130	-.099		.169
	(.271)	(.290)		(.351)
Log of Original Income	-.086	-.091		-.148
	(.104)	(.112)		(.144)
Neighbourhood effect	.075*	.090*		.093*
	.000	(.046)		.000
Lagged value of take-up	1.978***	1.990***	1.338***	1.328***
	(.058)	(.064)	(.083)	(.084)
Initial Value		.403***	1.652***	1.699***
		(.075)	(.149)	(.152)
	-1.734***	-1.793***	-2.322***	-2.473***
	(.487)	(.525)	(.624)	(.653)
/				

var(_cons[idperson])		.161**	.653***	.671***
		(.071)	(.131)	(.135)
Observations	7723	7723	7723	7723
ll	-1957.594	-1952.935	-1813.524	-1798.137
Wald test	2245	1605	899	926
p	.000	.000	.000	.000
rho		.139	.395	.401

*Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level. Standard errors are in the brackets.*

Table B5. Probability of Claiming CB, alternative take-up measure dynamic probit model

	CB		CB – Alternative Measure	
Log Simulated Eligible Amount	.133***	(.028)	.142***	(.028)
Age	-.069*	(.038)	-.062*	(.036)
Age2	.001*	(.000)	.001*	(.000)
Gender (Base: Female)				
Male	-.049	(.079)	-.094	(.078)
Marital Status (Base: Married/Cohabitating)	-.056	(.249)	-.135	(.242)
Separated, Divorced, Widowed	-.477	(.347)	-.631*	(.330)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African Asian	.067	(.245)	.093	(.247)
Asian or Asian British Chinese	.047	(.135)	.023	(.129)
Black or Black British	-.047	(.172)	-.075	(.169)
Arab and any other	-.415	(.406)	-.401	(.424)
Health (Base: Not Disabled)				
Disabled	-.109	(.221)	-.127	(.209)
Children in Household (Base: One)				
Two	-.115	(.421)	-.202	(.413)
Three or more	-.113	(.484)	-.308	(.472)
Minimum age of child in household	-.392***	(.150)	-.459***	(.145)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	-.049	(.156)	-.105	(.156)
Education (Non-Tertiary)				
Tertiary	-.053	(.069)	-.039	(.067)
Number of rooms in dwelling	-.151***	(.046)	-.155***	(.045)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.034	(.107)	-.013	(.100)
Rented	-.088	(.103)	-.076	(.102)
Reduced Rented	-.274	(.352)	-.456	(.346)
Social Rented	.029	(.123)	.036	(.122)
Free	-.179	(.297)	-.160	(.293)
Other	-.371	(.480)	-.299	(.514)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	-.301	(.332)	-.353	(.332)
Technical and Skilled Roles	-.357	(.329)	-.347	(.329)
Service Manual and Support Roles	-.114	(.407)	-.176	(.408)
Log of Original Income	.236*	(.132)	.240*	(.134)
Neighbourhood effect	.080*	(.045)	.074*	(.044)
Personality Traits				
Openness to Experience	-.008	(.040)	.015	(.038)
Conscientiousness	-.045	(.041)	-.042	(.040)
Extraversion	-.009	(.035)	-.024	(.035)
Agreeableness	.016	(.036)	.028	(.035)
Neuroticism	-.007	(.038)	-.007	(.037)
Cognitive Ability	-.020	(.037)	-.016	(.036)
Time Effects (Base: 2011)				
2012	.379**	(.157)	.365**	(.153)
2013	.079	(.141)	.067	(.138)
2014	.248*	(.139)	.192	(.135)
2015	.187	(.130)	.187	(.126)
2016	.217*	(.120)	.219*	(.116)
2017	.287**	(.118)	.288**	(.115)
2018	.060	(.123)	.058	(.120)
Time-average varaibles				
Responsible for housing costs	.000	(.167)	.059	(.168)

Single	.065	(.262)	.005	(.255)
Separated, Divorced, Widowed	.404	(.403)	.498	(.391)
Two	-.122	(.181)	-.055	(.171)
Three or more	-.084	(.287)	.081	(.277)
Minimum age of child in household	.242	(.168)	.284*	(.164)
Professional and Managerial Roles	.819*	(.452)	.805*	(.448)
Technical and Skilled Roles	1.038**	(.444)	.964**	(.442)
Service Manual and Support Roles	.998*	(.515)	1.052**	(.514)
Log of Original Income	-.639***	(.236)	-.626***	(.231)
Neighbourhood effect	.001	(.048)	.005	(.047)
Receipt of LB/UC (Base: Not in receipt)				
Receipt	.807***	(.122)	.835***	(.120)
Lagged Take-up	1.785***	(.107)	1.754***	(.107)
Age of Child is 16	.272	(.387)	.262	(.386)
Lagged Take-up x Age of Child is 16	-.449***	(.162)	-.509***	(.161)
Initial take-up	1.726***	(.176)	1.829***	(.173)
Constant	.092	(.953)	.008	(.922)
lnsig2u	-.604***	(.205)	-.580***	(0.197)
Observations	16,009		16,567	
sigma_u	.739		.748	
rho	.353		.359	
ll	-1862.800		-1977.651	

Table B6. Probability of Claiming LB/UC, alternative take-up measure dynamic probit model

	LB/UC		LB/UC – Alternative Measure	
Log Simulated Eligible Amount	.318***	(.038)	.314***	(.036)
Age	-.017	(.029)	-.014	(.029)
Age2	.000	(.000)	.000	(.000)
Gender (Base: Female)				
Male	.248**	(.109)	.229**	(.107)
Marital Status (Base: Married/Cohabitating)	.539***	(.177)	.540***	(.176)
Single				
Separated, Divorced, Widowed	.255	(.231)	.311	(.235)
Ethnicity (Base: White)				
Mixed: White and Black Caribbean Black African Asian	.150	(.241)	.170	(.244)
Asian or Asian British Chinese	.146	(.142)	.180	(.142)
Black or Black British	-.170	(.135)	-.156	(.133)
Arab and any other	.099	(.590)	.120	(.594)
Health (Base: Not Disabled)				
Disabled	.160	(.178)	.182	(.174)
Children in Household (Base: One)				
Two	.354**	(.162)	.373**	(.160)
Three or more	.825***	(.271)	.779***	(.266)
Minimum age of child in household	-.368***	(.136)	-.377***	(.134)
Housing Cost (Base: Not responsible)				
Responsible for housing costs	.105	(.151)	.141	(.153)
Education (Non-Tertiary)				
Tertiary	.010	(.080)	-.030	(.078)
Number of rooms in house	.043	(.065)	.024	(.062)
Housing Tenure (Base: Owned on mortgage)				
Owned outright	.081	(.126)	.047	(.124)
Rented	.351***	(.097)	.372***	(.096)
Reduced Rented	.160	(.220)	.131	(.212)
Social Rented	.624***	(.105)	.635***	(.103)
Free	.643**	(.306)	.736**	(.313)
Other	-.075	(.678)	-.010	(.692)
Labour Market Status (Base: Inactive, Unemployed, Sick, Disabled, Student)				
Professional and Managerial Roles	-.238	(.276)	-.152	(.270)
Technical and Skilled Roles	-.097	(.231)	-.096	(.227)
Service Manual and Support Roles	.043	(.288)	.024	(.282)
Log of Original Income	-.287**	(.122)	-.267**	(.118)
Neighbourhood effect	-.009	(.053)	.012	(.053)
Personality Traits				
Openness to Experience	-.031	(.039)	-.024	(.038)
Conscientiousness	-.042	(.041)	-.033	(.041)
Extraversion	.042	(.038)	.027	(.037)
Agreeableness	.004	(.040)	-.006	(.040)
Neuroticism	.060	(.038)	.058	(.037)
Cognitive Ability	.046	(.042)	.050	(.042)
Receipt of LB/UC (Base: Not in receipt)				
Receipt	.475***	(.092)	.461***	(.088)
Lagged Take-up	1.328***	(.084)	1.196***	(.081)
Initial Value	1.699***	(.152)	1.910***	(.145)
Time-average variables				
Responsible for housing costs	-.171	(.172)	-.224	(.174)
Single	.655***	(.198)	.624***	(.197)
Separated, Divorced, Widowed	.515**	(.238)	.484**	(.238)

Two	-.291	(.184)	-.265	(.182)
Three or more	-.320	(.286)	-.247	(.281)
Minimum age of child in household	.434***	(.152)	.428***	(.150)
Professional and Managerial Roles	.102	(.343)	.046	(.335)
Technical and Skilled Roles	.254	(.301)	.314	(.294)
Service Manual and Support Roles	.169	(.351)	.281	(.344)
Log of Original Income	-.148	(.144)	-.162	(.144)
Neighbourhood effect	.093*	(.056)	.078	(.055)
Time Effects (Base: 2011)				
2012	.353**	(.149)	.359**	(.147)
2013	.508***	(.145)	.516***	(.143)
2014	.512***	(.140)	.489***	(.138)
2015	.394***	(.139)	.345**	(.138)
2016	.410***	(.137)	.429***	(.135)
2017	.318**	(.136)	.318**	(.133)
2018	.158	(.131)	.186	(.130)
Constant	-2.473***	(.653)	-2.642***	(.650)
Observations	7723		8002	